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The Science behind the COVID Pandemic and Healthcare Technology Solutions

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The Science behind the COVID Pandemic and Healthcare Technology Solutions

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Foreword by The Series Editor

The Science behind the COVID Pandemic and Healthcare Technology Solutions

The COVID world pandemic started in 2019, allegedly from a wild animal at an animal market in the city of Wuhan, China, and by mid-2022, there were already 6 million deaths and more than 600 million cases worldwide (https://coronavirus.jhu.edu/map.html).

Scientists were puzzled as they did not know much about the virus which caused COVID and they were also puzzled by the rate of mutations of the virus. In the middle of 2022, there were still hundreds of thousands of new cases every day, despite the high rate of vaccination of the population (by mid-2022 there were 12 trillions of doses administered). With the use of the urgently developed vaccines, in some parts of the world people have been vaccinated even four times.

Many questions were raised during this pandemic, such as

– Why such an advanced Civilization, inhabiting the Earth, became suddenly threatened by a simple virus?
– How can Science help understand the genetic code and the mutations of it, and can, in turn, develop means to save the Planet?
– What new technologies need to be developed for this purpose?-What would be future consequences of a "weakened" world population?
– As humans share the Earth with other humans and with animals, both domesticated and wild, do they need to change the way of coexistence?
– The human body hosts millions of viruses and trillions of bacteria, still in a peaceful way, do we need to worry about that in the future?

Humans live on this Planet with millions of other species of animals, viruses, bacteria, plants, and fungi in a symbiotic way and each of these species exist in their own genetic and behavioral space. The main question of all is how do we preserve this symbiosis for the future generations? And the answer is through advancement in Science and Technology.

Those and more other questions are raised and addressed in this world-first systematic and comprehensive volume, revealing the Science behind the COVID and the Technologies that can be used to study and overcome the pandemic. Issues and topics covered in the volume include contact tracing, machine learning for automatic detection of respiratory symptoms, telemedicine, using wearable and smart technologies, using mobile phones, non-invasive thermal technologies, radiographs, and Artificial Intelligence in diagnosis.

And most importantly, this volume discusses the concept of "new normal life" and how societies and individual will be affected by this "new normality".

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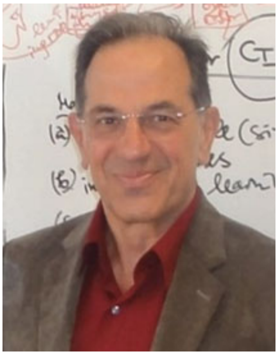

Nikola K. Kasabov is Professor of Knowledge Engineering and Founding Director of the KEDRI at Auckland University of Technology (AUT), New Zealand and also George Moore Chair Professor at Ulster University, UK. He is Life Fellow of IEEE, Fellow of the Royal Society (Academy) of New Zealand, Fellow of the INNS College of Fellows, Honorary Professor at the Teesside University UK and the University of Auckland NZ, Doctor Honoris Causa from Obuda University, Hungary. He holds a Master's degree in Engineering and Ph. D. in Mathematics from TU Sofia, Bulgaria. He has published more than 700 works in the areas of neural networks, computational intelligence, evolving connectionist systems, neuro-informatics, and bioinformatics. He is a Past President of the INNS and APNNS (Asia-Pacific Neural Network Society). He is the Editor-in-Chief of the Springer Series on Bio- and Neurosystems.

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Prof. Abbas Rajabifard, Ph.D., FIEAust, Hon. FSSSI is an internationally recognized scholar and geospatial engineer. He is an active leader in land and geospatial intelligence and disaster resilience and sustainability. He is Director of Smart and Sustainable Development and Academic Lead Infrastructure Platform, Faculty of Engineering and IT, the University of Melbourne. He was Chair of the United Nations Global Geospatial Information Management Academic Network. He has led multiple projects improving resilience and resilience impact in poverty-stricken areas, and international governments particularly in the Asia-Pacific, Europe, North America, and Latin

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Technology-Driven Pandemic Monitoring Applications

The Science behind the COVID Pandemic and Healthcare Technology Solutions: An Introduction

Sasan Adibi, Abbas Rajabifard, Sheikh Mohammed Shariful Islam, and Alireza Ahmadvand

Abstract Since December 2019, with the emergence of a new family of coronaviruses named SARS-CoV-2 a global outbreak took the whole world by surprise. It soon started overwhelming the global healthcare systems, with its numerous waves and the emergence of new virus variants, making the management of the pandemic extra challenging. The fast-changing dynamics of COVID-19 pandemic gave us the opportunity to assess our healthcare infrastructure in a systematic way. There was also a growing need and desire for technology-assisted interventions to keep us safer in public spaces. To address the challenges presented by COVID-19 pandemic, this book aims to present the latest technology advances tested and utilized for the management of the current global pandemic. It further aims to propose a potential roadmap on how to move forward, develop new technology-driven paradigms and solutions, and elucidate the roadmap towards normalcy, with hopes to continue living gracefully with the help of technology while accepting the existence of this virus in our societies. In this introductory chapter, we aim to provide insights into the topics presented in various sections and chapters of this book, which is comprised of the following sections: Technology-driven pandemic monitoring applications, Non-invasive COVID-19 detection and diagnostic systems, Decision-making analytics for COVID-19, Psychological and educational interventions in COVID-19 pandemic, Location intelligence and community resilience in pandemic situations, and Future directions and roadmaps.

Keywords Introduction · Chapter review · Book overview

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In December of 2019, a new family of coronaviruses, labeled as “novel coronavirus” or SARS-CoV-2 emerged. The appearance of this new outbreak took the whole world by surprise and soon started overwhelming the healthcare systems globally by a sudden influx of patients requiring urgent medical assistance. Since then, the COVID-19 pandemic has gone through numerous waves and the emergence of new virus variants has made the management of this pandemic extra challenging.

The fast-changing dynamics of COVID-19 and the resulting pandemic have given rise to the important opportunity of looking at our healthcare infrastructure in a systematic way. In some areas around the globe, cities have gone through multiple waves of COVID-19 and there has been a growing dire need and desire for technology-assisted interventions to keep us safer in public spaces. This can be achieved by assessing the well-being of the technology users as well as receiving constant updates from public health and government agencies, plus incorporating predictive mechanisms to issue a warning at times of possible outbreaks. In addition, while global communities and businesses are trying to adapt to the COVID-19 pandemic, location mapping tools and information are widely used by health departments, safety and emergency management authorities and wider professionals worldwide for gathering and analyzing data for supporting informed decisions.

To address the challenges presented by COVID-19 pandemic, this book aims to present the latest technology advances tested and utilized for the management of this global pandemic. It also aims to propose a potential roadmap on how to move forward, develop new technology-driven paradigms and solutions, and elucidate the roadmap towards normalcy, with hopes to continue living gracefully with the help of technology while accepting the existence of this virus in our societies.

This book is comprised of the following sections:

- Technology-driven pandemic monitoring applications
- Non-invasive COVID-19 detection and diagnostic systems
- Decision-making analytics for COVID-19
- Psychological and educational interventions in COVID-19 pandemic
- Location intelligence and community resilience in pandemic situations
- Future directions and roadmaps.

In this introductory chapter, we aim to provide insights into the topics presented in various sections and chapters.

1 Section I: Technology-Driven Pandemic Monitoring Applications

During the first waves of COVID-19, and before the availability of approved vaccines, monitoring the status of transmission and severity of the infection throughout different geographical areas was managed through regional and distributed contact tracing approaches, including QR code check-ins and updating the list of hot spot infection sites or super spreader locations.

The first section of this book reports on the healthcare technologies used for contact tracing, testing, and pandemic control based on smartphone applications. This section includes 8 chapters describing contact tracing tools and techniques for proximity tracing, outbreak response, and symptoms tracking:

Chapter 2. *Pandemic's Behavior of One Year in Six Most Affected Countries using Polynomial Generated SIR Model.*

In this chapter, the behavior of the pandemic is studied in six most COVID affected countries of the world with the focus on the effectiveness of recovery rates, rate of infection of the virus, total active cases, deceased cases and recovered cases.

Chapter 3. *Digital Contact Tracing for COVID 19: A Missed Opportunity or An Expensive Mess.*

Despite the rapid adoption of digital contact tracing worldwide, there have been several causes for disparity in utilization of the technology, including privacy and accuracy concerns, which are discussed in this chapter.

Chapter 4. *A Re-configurable Software-Hardware Convolutional Neural Networks (CNNs) Framework for Automatic Detection of Respiratory Symptoms.*

This chapter addresses the early diagnosis of respiratory conditions using low power scalable software and hardware involving end-to-end convolutional neural networks (CNNs). This is achieved by proposing a scalable multimodal CNN software-hardware architecture.

Chapter 5. *A Comprehensive Telemedicine Service in Hong Kong Provided Through a Mobile Application.*

This chapter highlights the experience of developing a telemedicine program for public healthcare services in Hong Kong.

Chapter 6: *Adapting to Live in the Global Pandemic Era: Case Studies.*

This chapter illustrates applications and solutions that can aid the adaptation processes of living in the global pandemic era, with case studies of security concerns and how quickly a new business can be introduced to cope in the era of the pandemic we are currently living in.

Chapter 7: *Towards QR Code Health Systems Amid COVID-19—Lessons Learnt from Other QR Code Digital Technologies.*

This chapter features the possibility of utilizing the QR code technology for health information systems to monitor the migration patterns of people, and to validate COVID-19 test results and vaccination certificates.

Chapter 8: *Optimal Testing Strategies for Infectious Diseases.*

In this chapter, six main guidelines are established, dictating estimated variance of prevalence and associated risk for inflow quotas allocation between population groups, as well as optimal posterior updates via classic confidence intervals and Bayesian methods.

Chapter 9: *Contact Tracing in Healthcare Facilities Using Bluetooth.*

This chapter describes a Bluetooth-based framework consisting of a heterogeneous architecture that supports contact tracing and exposure notification in hospitals and nursing homes, while meeting the required level of accuracy and privacy.

2 Section II: Non-Invasive COVID-19 Detection and Diagnostic Systems

In the context of COVID-19 detection and diagnosis, non-invasive methods refer to a class of intervention systems used for managing COVID-19 pandemics by minimally engaging with the subjects in a physical sense, such as utilizing image, video, and other types of waveforms. This is very convenient for the subjects (the people being monitored) as well as in public health scenarios, where scalability may be supported through such non-invasive approaches.

The second section of the book focuses on non-invasive technologies for diagnosis and detection of COVID-19, and also on preventive measures. It includes four chapters covering the topics of: smart materials, non-invasive physiological markers, bedside gadgets, and patient-centric wearable devices.

Chapter 10: *Monitoring the Health and Movement of Quarantined COVID-19 Patients with Wearable Devices.*

In this chapter, a prototype wearable device and a cloud-server solution are proposed, which were tested for their usability. The findings suggest that this device can assist in the remote monitoring of the location and health condition of quarantined people.

Chapter 11: *Context-Aware and User Adaptive Smart Home Ecosystems Using Wearable and Semantic Technologies During and Post COVID-19 Pandemic.*

This chapter provides evidence-based applications and a comprehensive understanding of the use of wearables and smart home ecosystems during and after COVID-19 pandemic for health care providers, researchers, students, and technology developers.

Chapter 12. *Wearable Tracking: An Effective Smartwatch Approach in Distributed Population Tracking During Pandemics.*

This chapter highlights a generalized approach for designing and developing wearable internet of things (wIoT) with enabled health technology solutions, which can act as predictive and real-time mechanisms to issue alarms and execute notifications, enhance context-aware location features, and promote contact tracing of the subject to promote early pandemic management procedures.

Chapter 13. *Making the Invisible Visible—A Science and Society View of Developing Non-invasive Thermal Technology.*

This chapter describes the development of a prototype for health intervention. It highlights the necessity to include interdisciplinary working practices between engineering and social sciences, and building an integrated body of knowledge, particularly in circumstances that require rapid response to global problems, such as COVID-19. It highlights socially-relevant topics such as ethics of health measures, privacy in surveillance situation and social equity in pandemic management.

3 Section III: Decision-Making Analytics for COVID-19

Decision-making analytics is a very diverse and multifaceted topic, which involves a number of key technical buzz phrases and disciplines, such as: data analytics, machine learning, artificial intelligence (AI), deep learning, and big data. These key technologies have been assisting researchers in almost any research areas to gather, classify, categorize, and make sense of the captured information. In the context of COVID-19, these key technologies have shown very promising results for important decision-making models and practices, such as contact tracing, vaccination, community assistance, and healthcare supports.

The third section of the book focuses on decision-making analytics for detection and management of COVID-19 interventions, and includes the following chapters:

Chapter 14. *EMD and Horizontal Visibility Graph-Based Disease Tagging for Covid-positive Chest Radiographs.*

This chapter describes preliminary steps in the ongoing implementation of horizontal visibility graphs (HVG) and related Hamming-Ipsen-Mikhailov (HIM) network similarity (distance) metric to provide automatic disease tag for normal and COVID-positive chest radiographs.

Chapter 15. *Mobility Analytics and COVID-19 in Greece.*

This chapter presents three main aspects of epidemic modelling in detail, with Greece and its SARS-CoV-2 outbreak during 2020–2021 as a use case. Epidemic monitoring and predictive analytics are discussed through the underlying system dynamics, as well as the limited availability of timely and reliable epidemic data.

Chapter 16. *Dynamical Modeling of Outbreak and Control of Pandemics: Assessing the Resilience of Healthcare Infrastructure under Mitigation Policies.*

This chapter introduces three dynamical methods applicable to the modeling of various aspects in healthcare infrastructures. The described model is applied to the analysis of the COVID-19 outbreak and mitigation strategies in the city of Izeh in Iran.

Chapter 17. *COVID-19 Diagnosis with Artificial Intelligence.*

This chapter briefly introduces Artificial Intelligence, its strong potential, and its capability of making manual procedures faster and more accurate during pandemics.

Chapter 18. *COVID-19 Features Detection using Machine Learning Models and Classifiers.*

In this chapter, different machine learning techniques are implemented to detect the features of COVID-19, including chest X-Ray and compuetd tomography (CT) medical images to identify lung infections.

Chapter 19. *Cough Detection using Mobile Phone Accelerometer and Machine Learning Techniques.*

This chapter focuses on investigating workable methods for automatic detection and classification of cough, which allow both identification of COVID-19 patients and their long-term monitoring.

4 Section IV: Psychological and Educational Interventions of COVID-19

Two hardest hit-areas by the COVID-19 pandemic have been the psychological and mental health of individuals and the larger societies, as well as the education sector. It is no surprise that the mental well-being of people has been impacted very early on in the pandemic, due to the extended lockdowns and limitations in social gatherings. The same impact was felt in the education sector as schools and universities rolled into online learning mode with little to no prior preparation, leaving millions of students off-guard to deal with the online education challenges.

The fourth section of the book discusses technologies to mitigate the negative psychological effects of pandemics and its impact on education.

Chapter 20: *Mental Healthcare in the 'New Normal': Digital Technologies for Pandemics.*

This chapter offers an overview of digital technologies to support mental health during the current and future pandemics. It analyses the mental health effects observed during the Covid-19 pandemic, highlighting social groups that are vulnerable to those effects and showing how digital technologies can help, now and in the future.

Chapter 21. *Innovations in Surgery—How Advances in the Delivery of Surgical Care and Training can Help Hospitals Recover from COVID-19.*

This chapter discusses how adopting technological innovations might help reduce the backlog of unmet surgical care. It examines how the shortfall in surgical training could be mitigated through technology-enhanced learning (TEL), based on extended reality (XR) tools.

Chapter 22: *A Biomarker-Based Model to Assist the Identification of Stress in Health Workers Involved in Coping with COVID-19.*

This chapter describes a theoretical study concerning the health of professionals who work on the front lines. It proposes a model based on some biomarkers for identifying and classifying stress levels. It discusses the possibility of integrating the model in a recommender system aiming at proactively proposing mitigation actions in the surveillance of occupational stress of those professionals.

Chapter 23: *Diagnosis and Management of Oral Maxillofacial Surgery and Dental Education During the Pandemic.*

This chapter deals with two topics: maxillofacial surgeons being prone to infections through respiratory droplet transmissions and close contact with their patients, and ways to deal with this problem, and e-learning dental training tool that can help to educate clinical staff, for example, to reduce such an exposure risk. It reviews different e-learning software and 3D environments for dentistry education and reviews different measures for patient management during pandemics.

5 Section V: Location Intelligence and Community Resilience in Pandemic Situations

Currently businesses are being tasked to push towards recovery post pandemic and take positive steps towards developing the agility required to stay on top of COVID-19 reemergence.

To that effect, location intelligence and spatial analytics are absolutely essential to strategically enable the leading enterprises to mitigate associated challenges and unlock invisible opportunities.

Therefore, the fifth section of the book covers the spatial and location intelligence, as well as community resilience, which are discussed in the following chapters:

Chapter 24. *Digitizing Pandemic Response Operations in a Resource-Poor Setting.*

This chapter demonstrates the possibility of digitizing the pandemic response management for effective control of the pandemic, in a resource-poor and logistically challenging environment. It examines the information and data flow concerning the business processes of the pandemic response, the technologies adopted and used in these processes and how these were used in the operations and decision making in the Maldives.

Chapter 25: *Resilience to COVID-19 Pandemic.*

This chapter defines a health resilience score to compare the performance of the countries in handling the COVID-19 outbreak. In addition, the causes and effects of stress on mental health and immune system during a pandemic are addressed. Techniques and strategies that reduce stress and increase resilience are also explained.

Chapter 26: *Use of Remote Sensing and GIS Techniques for Adaptation and Mitigation of COVID-19 Pandemic.*

In this chapter we discuss the use of advanced tools, such as Geographic Information Systems (GIS) and Remote Sensing (RS) to devise adaptation and mitigation strategies to control such pandemics. Case studies from various states of India are discussed to explain the controlling strategies which can be developed from these tools and techniques.

Chapter 27: *Mapping Blockchain Technology Prospects and Solutions in the Healthcare Industry for Pandemic Crises.*

This chapter covers fundamental aspects of blockchain technology and its applications within the healthcare industry, particularly targeting smart monitoring systems based on wearables that can provide updates about the individual's health-related conditions (e.g., blood pressure, temperature, location, etc.) to physicians and monitoring agencies.

6 Section VI: Future Directions and Roadmaps

The COVID-19 pandemic was the biggest global challenge we have faced in recent years and graceful emergence from this dire strait, requires a multifaceted international harmony, collaboration, and participation.

The sixth and last section of the book covers lesson learned from the current approaches to manage the pandemic and the roadmap to tackling the next generation pandemic management systems, which are discussed in the following final five chapters:

Chapter 28: *The Role of Healthcare in the Post-Pandemic Era—"COVID Normal".*

This chapter discusses the impact of the pandemic on healthcare industry and how to adapt to the post-pandemic era by modifying the current healthcare management to enable a smooth transition and enhance the healthcare system to combat future pandemics.

Chapter 29: *Scenario Assessment for COVID-19 Outbreak in Iran: A Hybrid Simulation-Optimization Model for Healthcare Capacity Allocation.*

This chapter investigates the effect of spatial units and factors affecting the prevalence of the COVID-19 and reaching an optimal capacity allocation in the health care centers by intervening in government decisions in Iran on disease control. This research is the first to analyze and develop a healthcare capacity allocation strategy by considering the mutual effects of disease outbreaks and government actions as decision aiding tools via a hybrid simulation–optimization framework.

Chapter 30: *Ensuring a Superior Level of Preparedness and Readiness by adopting a Knowledge-based Network-Centric approach Leveraging Information Systems for Emergency and Disaster Management.*

This chapter offers a new approach to emergency and disaster management such as the COVID-19 pandemic grounded in information/knowledge needs based on the combination of the doctrine of network-centric operations. The presented framework provides appropriate guidance and support for decision-making in real-time, facilitates the flow of factual information and knowledge among all stakeholders, and assists in eliminating disinformation as a factor in decision-making.

Chapter 31: *mHealth Systems and Applications in Post-Pandemic Healthcare.*

This chapter discusses the available contact tracing apps and their technical specifications. Several mobile health (mHealth) apps are discussed, including an overview of the opportunities and challenges of mHealth systems dealing with pandemics.

Chapter 32: *Synergistic Effects of Environmental Factors on the Spread of Corona Virus.*

This chapter investigates workable methods for automatic detection and classification of cough for long-term activity monitoring and identification of patients. An early diagnostic tool in the form of a mobile phone application is used to identify the severity of the disease and to indicate the need and urgency for hospitalization.

Chapter 33: *CFD Analysis of COVID-19 Dispersion via Speaking, Breathing, Coughing, and Sneezing.*

This chapter investigates the mechanism by which, majority of respiratory diseases spread, which is typically based on droplet production and associated physical processes, including fluid instability, breakup, and droplet conversion. The feasibility of this study is achieved using Computational Fluid Dynamics (CFD) tool through accurate simulations. The outcomes of this study can be extended to study future pandemics driven by other respiratory illnesses.

Chapter 34: *COVID-19 Pandemic: Lessons Learnt and Roadmap for the Future.*

This is the final chapter of the book, which discusses the key technological steps towards future post-pandemic directions.

Pandemic's Behavior of One Year in Six Most Affected Countries Using Polynomial Generated SIR Model

Monika Verma and Phalguni Gupta

Abstract In this chapter, the behaviour of the pandemic has been studied for the six most COVID affected countries of the world. The time period considered for the study is one year between April 1, 2020 and March 31, 2021. At the times of uncertainty, the mathematical models play a decisive role in shaping and designing the policies of the government. The characteristics of the pandemic are primarily measured with respect to the number of positive cases, deceased cases, recovered cases, active cases and test cases per day. On this set of data, polynomials of different degrees are plotted to obtain the best fit model of the data. The fitted models are analysed using three statistical parameters namely Root Mean Square Error (RMSE), χ^2, and R^2 Error. It has used Polynomial Generated SIR Model to determine various epidemic parameters like the basic reproduction number, recovery rate, rate of infection of the pathogen and the likes. The comparative tests are done and they reveal the accuracy of the developed model. The behaviour of the pandemic is observed to be different for different countries according to the recovery rates of the infectives, rate of infection of virus, total active cases, deceased cases and recovered cases.

Keywords Coronavirus · Mathematical modelling · SIR model · Beta · Alpha and delta parameters · Root mean square error · χ^2 · R^2 error

1 Introduction

New challenges always lie a step ahead of human thinking. Right from the Plague of Justinian to 2019-nCoV, human race has been encountered with numerous emerging pathogens of various orders. Zoonotic diseases are a health hazard if not controlled. The continuing threat of the spread of 2019 n-CoV would change the history of mankind to new normal (social distancing, mask wearing, changing patterns of education, altering the nature of jobs etc.). The epidemic of COVID-19 has the origin in Wuhan, China in December of 2019 in a "wet market" where live animals

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were being sold such as bats, dogs etc. Within few months the contagious virus has set its foot almost everywhere in the world. As per the World Health Organisation (WHO), almost the entire population of the world has been affected by the said virus. On February 12, 2020, WHO has officially named the disease caused by the novel coronavirus as COVID-19.

The 2019-nCoV (novel Corona Virus) is one of the seven members of coronavirus family that causes respiratory disorders ranging from mild infection to even death in humans. The four members of the coronavirus family, viz. 229E, OC43, NL63 and HKU1, cause common cold symptoms while the two other strains—severe acute respiratory syndrome coronavirus (SARS-CoV) and Middle East respiratory syndrome coronavirus (MERS-CoV) are zoonotic in origin and are fatal. Bats and camels are the potential hosts of MERS-CoV whereas racoon dogs, ferret badgers carry SARS-CoV. The coronaviruses are extensively spread over the entire planet and their genomes frequently combine to form new variants resulting in the periodical arrival of the infections [1].

Either through direct transmission from infected persons or through the contact from inanimate objects or through an airborne transmission, the SARS-COV-2 coronavirus can enter the susceptible persons and make them infectives. The symptoms, diagnosis, management, treatment (SDMT) is looked after once a person contracts to the disease [2]. As the infections caused by the virus is exploding at a fast pace, the different phases of SDMT post a challenge to the all the concerned subjects whether it be the infective persons or the susceptible persons or the hospitals or the government. The preventive methodology of vaccinating the entire population or isolation of infected persons or curbing the disease at the containment zone offers a large challenge till now.

The re-emerging lethal zoonotic diseases of these orders are conforming to the future where the pandemics would become more common and the preparedness of the governments and the concerned authorities would play a major role in handling the intervention approaches. One of the key roles in this preparedness depends on the mathematical models.

2 Mathematical Models

To predict the future of 2019-nCoV worldwide for each and every country, quite a good number of mathematical models have been proposed in the literature. They can prove to be helpful for governments to stop or minimize the spread of the pandemic and also to see the effects done by the epidemic. The government can then take proper measures for controlling the impact of the virus in general on the public and can reduce the dreadful consequences of the same. Mostly these epidemiological models are a boon in the crisis which the world is currently facing at present.

The main issue of concern is what needs to be estimated through these models. The predictions can be made on a wide variety of subjects. The projections which these models can predict would help the health care department to look into the various issues like the number of ICU beds, the number of ventilators, the number of health care persons needed in the hospitals, the medical instruments needed for curing the patients, the medicines required, when would the next peak of coronavirus expected, when would the offices, schools and the colleges be opened and when they will be in working condition. The short-term projections are better in comparison to long term predictions as the parameters change unexpectedly in each upsurge of the wave of COVID-19. If we want to predict/analyse the parameters for different countries, the mathematical models cannot predict accurately as:

1. The strictness of social distancing norms which are considered for one country cannot be applied for another country
2. There may be the parameters which are true in the first wave of some country but are not applicable for the second wave of same country
3. Data is not properly reported and the data is underreported
4. Models do not consider a possibility of the second wave [3].

With all these considerations, two types of models are used for predictions and they are simple mathematical models and complex mathematical models. The simple mathematical model does not take into consideration some of the parameters like the ways in which the virus is continuously upgrading itself to spread itself in an effective way, the way in which human population behaves when there is no lockdown, the undetected test cases, whether government policies are followed or not and so on. They simply work on the data that is statistically provided such as the number of positive cases, the number of active cases, number of death cases and test cases.

At the same time, the complex mathematical models are dependent on a more detailed account of the pandemic and they can create the impression of reality as they are considering many parameters such as which age group is getting affected, comorbidity factors such as diabetes, cancer, the risk factors as smoking, pollution levels at a particular place, the population distribution and the likes.

The possibility of correct outcomes in a complex model is also rare because the input are dependent on various factors that are difficult to manage in a particular time as well as the parameters required by the complex model is quite difficult to count and tally. With changing times, the collected input may not be accurate and valid in the near future and that is why instead of calculating single numbers and also to encompass the variations, the range must be given as the results predicted cannot have accurate input.

The assumptions made in the mathematical epidemiological model should be very evident and those parameters that are known but not as such are encompassed in the model should be described with their qualitative implications. The model should be such that it should be able to incorporate the accuracies when the data is uploaded as it keeps on becoming better and better with time. Lastly the models should be such that they should give appropriate warnings to avoid the misinterpretations arising from the forecasts that the model depicts.

As the epidemic does not follow exactly the same trends everywhere, the models should take some local considerations also. The mathematical models are becoming important for predictions as the number of deaths is increasing at an alarming rate globally. Earlier the models predicted the areas in which the pandemic is likely to spread, for how much duration the virus circulated in a particular community, the number of death cases, all these predictions are found to be helpful before the onset of the spread.

In the current scenario, the mathematical models play a vital role in forecasting the seriousness of the disease, at which scale the pandemic is spreading, how to use the limited resources, the way the government policies are getting changed with time, as the duration of lockdown, banning the public gatherings, going to the temples, restricted people's movement keeps on changing. If one follows the predictions of the mathematical modelling then it is expected that the number of death cases can be reduced, overall scenario can be made better.

Epidemiological mathematical models are best when they are using an adaptive science approach to include the sociological as well as anthropological work. A triangulation approach of the three needs to be developed. In this approach, the input is attuned to the contexts of many factors like ethnography, social conditioning and the local expertise. The output of the models should map to the new context inputs. As the effects would be seen socially and materially the parameters of predictions also include the way in which n-CoV spreads in a given area, which age group is being affected, whether the people are following the social distancing norms properly or not, whether the number of persons who needs the hospital is on the upsurge trend or is there a diminution in the trend of hospitalization.

The longer the time of the pandemic, the better the raw data obtained through which better predictions can be made. First of all, there should be a numerical stability and reliability in these predictions which is quite difficult to achieve due to numerous factors including the speed at which the virus is mutating, the general health of the public, which age group is being looked at and the likes, this output should be traced when they become a part of public life or they form an important part in forming the policies of the locality/government. While following the adaptive science approach, we have to look what is the impact of the use of models in context with the intervention of the government with respect to the general health of the public, the forecasting of the diseases. As the stakeholders are there in every scenario, the models should comply with developing concerns through changing times of the pandemic. Local matters are also a part of concern when there is causality so the modelling using adaptive approach should also pay attention to these things of apprehensions [4].

Telles et al. [5] have recommended that social distancing of 1–2 m and usage of masks with the disinfectants are useful measures for preventing and controlling the pandemic behaviour. In [6], Khalid et al. have focused on the implication of using zinc as the immune function. In [7], the authors have shown the possibility of using wavelets to measure the effect of COVID-19.

In this chapter a model has been used to calculate and analyse the different parameters for six, countries so that the different aspects of the pandemic can be seen clearly and based on it some standpoints can be taken.

2.1 Susceptible-Infected-Recovered (SIR) Model

SIR (Susceptible-Infected-Recovered) model and its variations are used by many authors around the world to predict the forecast of the said disease. The model in combination with genetical algorithm has been proposed by Rodrigues et al. [8]. Considering the age-related information, Singh and Adhikari [9] have studied a hybrid SIR model. Hybrid model of SIR with three phases is used by Chaves et al [10] to determine the reproduction number. To forecast the Pandemic in India, Dhanwant and Ramanathan [11] have worked on a SIR approach by using the SciPy software. SIR model with statistical machine learning has been used by Das [12] to predict the pandemic in China and India.

An approach of Bayesian methodology together with SIR is used for prediction of cases in Brazil by de Oliveira et al. [13]. Postnikov [14] SIR model combined with logistic Equation using the MATLAB software has been used to guess the COVID-19 spread in different countries. Using SIR model, Deo et al. [15] have predicted the subtleties of COVID-19 epidemic in India, Hazem et al. [16] have done the same in six countries of the world, while Jakhar et al. [17] have analysed and calculated the pandemic cases for 24 different states of India. Mujallad and Khoj [18] have studied COVID-19 cases in Makkah and Saudi Arabia.

Lopez and Rodo [19] have used SEIR (Susceptible-Exposed-Infectious-Removed) model by enlisting multiple scenarios in Spain and Italy. SEIR with artificial intelligence approach is employed by Yang et al. [20] to forecast outbreaks in China with the time-slice data. Stochastic SEIR model is used by Engbert et al. [21] to forecast the spread of COVID-19 in Germany. A general SEIR model for COVID-19 cases has been employed by Godio et al. [22] to compare cases in Italy, Spain and South Korea. SEIR with regression is analysed to predict the COVID-19 cases in India by Pandey et al [23]. SEIR has emphasized the operative contact rate of pandemic cases in India and has related the results with six other countries. With SEIR, Bonnasse-Gahot et al. [24] have monitored the bed obtainability in France. Using three features of regression, smoothing and age structure, through SEIR model, Dixit et al. [25] have predicted the pandemic. SEIR model of the pandemic for twelve countries is employed by Kohanovski et al [26]. A time dependent SIER modelling has been developed by Teles [27] for the country of Portugal. SEIR with auto regression is studied for epidemic cases in India by Wagh et al [28].

Ray et al. [29] have used extended SIR model for studying the lockdown in India to predict the role of interventions. Cruz and Cruz [30] have modelled SEIR-A (Susceptible-Exposed-Infected-Recovered-Asymptomatic concentration) for the analysis of the COVID-19 outbreak in one of the states of Brazil. Using the SS-SIR (State-Spate-Susceptible-Infected-Recovered) model, Kobayashi et al. [31] have analysed the intervention effect of the Pandemic in Japan. By means of SEIARD (Susceptible-Exposed-Infected-Asymptomatic-Recovered-Dead) model, de Leon et al. [32] have predicted the pandemic results of Mexico. SIR(D) dynamical model is used by Rajesh et al. [33] for the analysis of data in India. SEIAR model for COVID-19 cases in India has been predicted by Khatua et al [34].

In the SIR model, the population is split into three categories: Susceptible, Infectives and Removed. All those persons who have contracted the n-CoV are termed as infectives, the public who has not yet been exposed to coronavirus are termed as susceptible, and all those who have been either recovered or dead are termed as removed. The removed people cannot cause any infection to the susceptible and therefore are not a hazard to the pandemic.

In this model, the basic reproduction number is an important number which is denoted by the alphabet R_0. Right from the way in which the infection grows in the body to the way the infection spreads in the society, the basic reproduction number captures all these features and then allows the health care persons to work accordingly. In any outbreak this reproduction number holds an important value. If the value of R_0 is less than one then the assumption is that the disease would wane out of its own, but if the number is greater than one then it signifies that the spread of the disease is exponential and necessary measures are needed to curb the spread. Larger the value of R_0, the worst is the situation for the public.

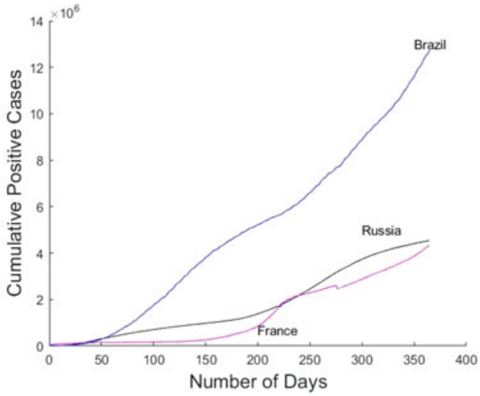
The estimates of the basic reproduction number at the beginning of the outbreak are found to be lying between 1.5 and 4.0. That means the entire human population could have been exploded with the disease if measures are not taken properly with time.

Figure 1 shows the cumulative number of positive cases for the six countries. As actions are taken, practically the exponential growth of the pandemic cannot continue its pace as there would be lesser interaction between the infectives and the susceptible. If no action is taken to control the spread of CoV then only 2% of the population would remain uninfected. The population size, the rate of infection and the death rate are the three components of the basic reproduction number. So, to control the spread of the pandemic, either rate of infection has to be reduced or the population has to be less or the number of recoveries have to be more. The difference between the basic reproduction number and the effective reproduction number is that the effective reproduction number is the average number of infections that are caused by the primary infected people. In either case, the number has to be less than one in order to wane out the outbreak.

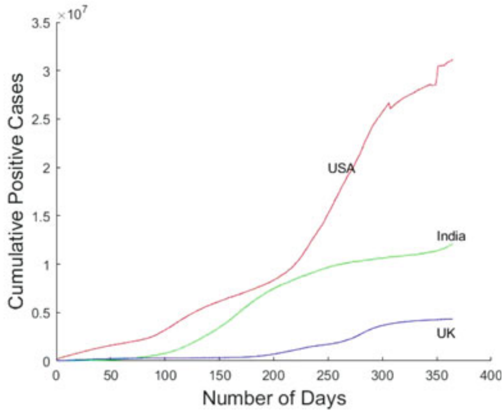
The total fatality rate is not dependent on the basic reproduction number as it does not tell the degree of dangerousness of the disease for an individual. Measles, for example, has a basic reproduction number which has an average value of 15 but is not deadly but the epidemic of EBOLA which has a reproduction number of 1.5 has caused more (approximately 60% of the total infected persons) number of deaths due to the disease.

In the case of COVID-19, the demographics of the population affected is worst in the case of older people. If the infection rate is high and fatality is low then the pandemic may end up killing more people but if the case fatality rate is high during pandemic, then it might create fear but it is less infectious as it might not get sufficient chance of spreading to the other people. The need to control the outbreak is best achieved when the number of susceptible are directly removed without having infection, i.e., by vaccination drive. It's often unfeasible to have vaccine in a suitable timeframe if it is spreading in full swing. So, isolation of infective patients and the

Fig. 1 Diagram of exponential rise of the pandemic of six countries



(a) Cumulative Positive Cases against Number of Days in three countries: Brazil, Russia and France



(b) Cumulative Positive Cases against Number of Days in three countries: USA, India and UK

quarantine of healthy people is used effectively to curb the spread. This chapter considers a simple model of SIR with polynomial generation for comparing the statistics of various countries. Comparison of various parameters of SIR model has been done. The model calculates the basic polynomial fitting of each country followed by SIR model to calculate the graphs.

The mathematical model SIR has been proposed by Kermack and McKendrick, in 1927 [35]. It has explained the dynamics of the communicable disease spreading amongst the susceptible persons in a very simple way which is diagrammatically shown in Fig. 2.

The SIR model describes three classes of the population as depicted in Fig. 2. They are the susceptible, the infectives and the removed. During any disease, people fall in any of these categories. The total population M is the summation of all the

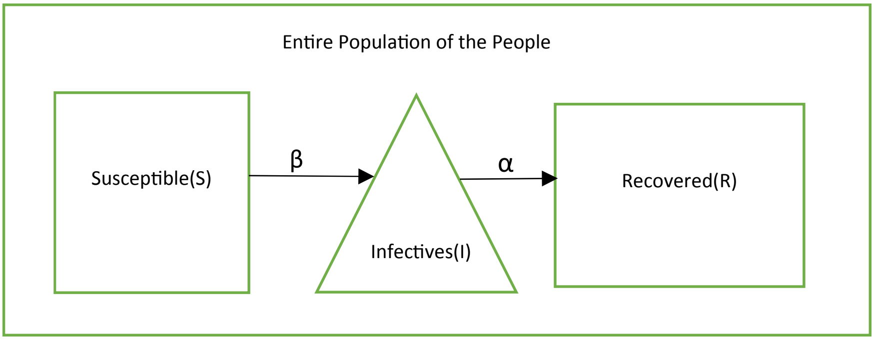


Fig. 2 SIR Model

infectives (I), susceptible (S) and removed (R). In the model, the rate at which the susceptible person changes into the infected person with respect to time is defined by Eq. (1). The rate depends on the susceptible as well as the infected persons. In this Equation, beta is the infection rate of the virus. With the increase of time, the number of susceptible would decrease; hence Eq. (1) has a negative value.

$$\frac{\mathrm{dS}}{\mathrm{dt}} = -\left(\frac{\beta}{\mathrm{M}}\right) * \mathrm{S} * \mathrm{I} \tag{1}$$

Equation (2) defines the rate of change of infection which is dependent on the rate of change of susceptible persons and the recovered patients. The rate at which the patients are recovered needs to be subtracted.

$$\frac{\mathrm{dI}}{\mathrm{dt}} = \left[\left(\left(\frac{\beta}{\mathrm{M}}\right) * \mathrm{S} * \mathrm{I}\right) - (\alpha * \mathrm{I})\right] \tag{2}$$

It can either increase or decrease with time. Alpha is the recovery rate of the infected persons. The rate of change of recoveries is shown in Eq. (3).

$$\frac{\mathrm{dR}}{\mathrm{dt}} = (\alpha * \mathrm{I}) \tag{3}$$

Initially, when there is no infection, the entire population is susceptible ($S = N$). This is depicted in Eq. (4)

$$\mathrm{dI}/\mathrm{dt} \sim (\mathrm{I} * (\beta - \alpha)) \tag{4}$$

while Eq. (5) shows the result after integration where I_0 is the number of infected patients at the time t and is a constant of the pandemic [36].

$$I = I_0 e^{(\beta-\alpha)*t} \tag{5}$$

If m has the value of $(\beta\text{-}\alpha)$ then Eq. (4) can be written as

$$\frac{dI}{dt} \sim m * I \tag{6}$$

And Eq. (5) can be written as

$$I(t) \sim I_0 * e^{m*t} \tag{7}$$

Integrating the Eq. (7), m is calculated. It is shown

$$IogI = (m * t) + (IogI_0) \tag{8}$$

The recovery rate of the infected persons is given by Eq. (9) at time t of the pandemic. I_0 tells the number of infectives at time t.

$$\frac{dR}{dt} = (\alpha * I_0) \tag{9}$$

By integrating Eq. (9), we obtain

$$\mathrm{R(t)} = (\alpha * \mathrm{t} * I_0) \tag{10}$$

Suppose, it takes $t = T$ time for a patient to recover then $R(T) = I_0$or $\alpha.T = 1$. Thus,

$$\alpha \approx 1/T \tag{11}$$

For a small change x in time the following two equations are obtained from Eq. (3)

$$\frac{R(t + x)}{x} = \alpha I \tag{12}$$

$$\alpha \approx \frac{R(t + 1) - R(t)}{I(t)} \tag{13}$$

The recovery rate (Alpha) can be found out directly from Eq. (13). In order to find out the maximum number of infected patients, we first divide Eqs. (2) and(3) as shown below

$$\frac{dI}{dt} / \frac{dS}{dt} = \frac{\alpha}{\beta} M\left(\frac{1}{S}\right) - 1 \tag{14}$$

$$\frac{dI}{dS} = \frac{\alpha}{\beta} M\left(\frac{1}{S}\right) - 1 \tag{15}$$

Integrating Eq. (15), one gets the maximum infected persons as.

$$I = -S + \left(\frac{\alpha}{\beta}\right) M ln S + C$$

Or

$$I = N - S + \frac{\alpha}{\beta} M ln \frac{S}{M} \tag{16}$$

To simplify Eq. (16), the assumptions $S = M_s$, $I = M_i$, $R = M_r$ are made (s is the part of total susceptible, i is the part of total infected and r is the part of total recovered) to obtain following equations

$$\frac{di}{dt} = i(\beta s - \alpha) \tag{17}$$

$$\mathrm{I} = 1 - \mathrm{s} + \left(\frac{\alpha}{\beta}\right) \ln s \tag{18}$$

During the highest number of infection rate $d_i/d_{\mathrm{t}} = 0$, s is now obtained shown in Eq. (19). If we substitute the value of s in Eq. (18), we get Eq. (20). Maximum number of infected patients can be found from Eq. (20).

$$s = \frac{\alpha}{\beta} \tag{19}$$

$$i_{max} = 1 + \frac{\alpha}{\beta}\left[\ln \frac{\alpha}{\beta} - 1\right] \tag{20}$$

Equation (18) can also be written as Eq. (21) at the end of the infection ($I = 0$), solving which we get the value of s. Equation (22) defines the Basic Reproduction number R_0 which is the ratio of spread of disease (alpha) and recovery rates.

$$1 - \mathrm{s} + \left(\frac{\alpha}{\beta}\right) \ln s = 0 \tag{21}$$

$$R_0 = \frac{\beta}{\alpha} \tag{22}$$

Hence, the different parameters of SIR model can be found out.

2.2 Polynomial Fitting Model

This section has used information on the number of test cases along with the number of positive cases, the number of deaths and the number of recoveries of the patients suffering from the COVID-19 which is available in [37]. If T_i and P_i are the number of test cases and that of positive cases on the ith day then the relative positive cases on the ith day, RP_i, is given by

$$\mathrm{RPi} = \frac{P_i}{T_i} \tag{23}$$

Again, if D_i, A_i are the number of deceased cases and that of active cases on the ith day then the relative deceased cases on the ith day, RD_i, is given by

$$\mathrm{RDi} = \frac{D_i}{A_i} \tag{24}$$

And if R_i, A_i are the number of recovered cases and that of active cases on the ith day then the relative recovered cases on the ith day, RR_i, is given by

$$RRi = \frac{R_i}{A_i} \tag{25}$$

And the active cases A_i are defined as

$$\mathrm{A_i = A_{i-1} + P_i - D_i} \tag{26}$$

Given the above defined relative data of the pandemic for n days, polynomial of various degrees has been obtained to find their best fits. To determine the best fitted polynomial for each case, we have used three statistical parameters, namely *RMSE*, R^2 and χ^2 and smaller the value of the error in a given polynomial, better the fit of the polynomial.

A. *RMSE (Root Mean Square Error)*

The root mean square error is the difference between the observed data against the predicted data after fitting on a polynomial over number of days [38]. If O_i and E_i are the observed and the predicted data on a polynomial in the ith day, respectively, then RMSE is defined by

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (O_i - E_i)^2}{n}} \tag{27}$$

B. R^2*(R squared)*

R^2 is another statistical parameter, known as the Coefficient of determination, is the relative variance in the dependent variable that is predictable from the independent variable(s). It is a measure to see how best the observed data are replicated by the model, based on the relative variation of data [39]. For a given set of n data, O_1, O_2, …, O_n, let P_j be the polynomial of degree j fitted on these data and E_i be the estimated value obtained from the polynomial P_j for the data O_i. Then the coefficient of determination, R^2, is defined by

$$R^2 = 1 - \frac{SS_R}{SS_V} \tag{28}$$

where SS_R, sum of squares of residuals and SS_V, sum of squares proportional to variance, are

$$SSR = \sum_{i=1}^{n} (O_i - E_i)^2 \tag{29}$$

$$SSV = \sum_{i=1}^{n} (O_i - \overline{O})^2 \tag{30}$$

where $\overline{O} = \sum_{i=1}^{n} O_i$.

It can be seen that in the best case, the estimated values are exactly same as the observed values for all days which results $SS_R = 0$ and $R^2 = 1$. A polynomial which always predicts $\overline{O}$ finds its R^2value as 0. Thus, larger the value of R^2, better the prediction polynomial. Some of other important properties of the coefficient determination, R^2, are

1. It helps to determine the ratio of how the expected value varies with respect to the observed data.
2. It helps to show the expected variation against the total variation.
3. It helps to show the relative association between observed and expected data.

C. χ^2 (Chi-square)

Pearson's χ^2 value is also used to see the goodness of fit of the polynomial for a given set of observed data. Smaller the value the better is the probability that the observed data fits the expected data well [40]. Suppose, there is a set of n data, O_1, O_2, …, O_n. Let P_j be the polynomial of degree j fitted on these data and E_i be the estimated value obtained from the polynomial P_j for the data O_i. The formula for the same can be written as

$$\chi 2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{31}$$

2.3 Polynomial Generated SIR (PG-SIR) Model

Polynomial Generated SIR (PG-SIR) model has been presented. First, the data of affected areas under study are used to obtain the best fit curve using the polynomial model and these polynomials are used to interpolate and extrapolate to obtain various data, like recovered cases, test cases, deceased cases, positive cases or the active cases. According to the statistical tests and calculations of various errors and the correlation between the two sets of data of various classes, corresponding polynomial fit are used in the SIR model to analyse the basic reproduction number, the maximum number of infected patients, the infection rate, contact rate and their corresponding graphs are plotted for all the affected areas considered for the study. One year is divided into three parts, each having four months. Comparison is done within the areas for different waves as well as amongst the different areas for different parameters. The PG-SIR model can predict the peaks/waves with great accuracy even with small amount of data of starting months. So, this model is used to analyse the peaks and to make policies in accordance with the predicted peaks. Steps of PG-SIR model are as follows:

1. Get total positive cases, recovered cases, test cases, deceased cases, active cases.
2. Calculate the relative positive, relative deceased and relative recovered cases.
3. Find the coefficients of the polynomials of various degrees.
4. Obtain the values of different errors RMSE, R square, Chi square error.
5. Obtain the best fitted polynomial to be used in the SIR model.
6. Calculate the various parameters such as Beta, Alpha, R_0, m, s.
7. Use these parameters to predict the next peak by PG-SIR model.

The results and analysis of the Polynomial Generated SIR (PG-SIR) model show the correct representation of the pandemic infection rate, recovery rate, the maximum number of infected persons, the fraction of susceptible persons, the difference between the transmission and the recovery rates and the basic reproduction number.

3 COVID-19 Scenario in Six Countries

This chapter considers six countries which have faced the extreme impact and major breakdown due to coronavirus. These countries are USA, India, Brazil, Russia, France and UK. The impact of vaccination among the citizens of any country has not been studied. The breakdown relates to the deteriorating health of the public, the increasing number of deceased cases in the various countries, the maximum number of peaks/waves of the deadly infection hitting these areas, the economic shattering of the nations, the devastating effects on education and the likes.

3.1 USA

In USA, the total population is 332,644,518 whereas the population density is 33.86/km^2. The area of USA is 9,161,923 km^2. The first case in USA is found on January 19, 2020 where a 35-year-old man is depicted with the symptoms of Corona Virus in Washington. SARS-COV-2 in United States of America has created havoc resulting in more than 601,000 deaths. Since January 2020 it has confirmed over and above 33.5 million confirmed cases [41]. COVID- 19 cases of USA are shown in Fig. 3.

Many cases have gone undetected together with 114.6 million infections which have covered almost one third of the United States population. The number of positive cases in USA has become the highest. And one fifth of the total worlds, confirmed cases and deaths are also reported to have occurred in USA. After heart disease and cancer, the infection caused by the coronavirus has become the third leading cause of death. The life expectancy has also dropped from 78.8 years to 77.8 years during the early months of 2020.

After the first case, the president of USA has declared the outbreak as Public Health Emergency. All measures have been taken to control the spread of the disease amidst the mess created by the sudden spread of the infection caused by the Virus. Measures like travel restrictions as well as the social distancing, lockdown, school closures and testing have become the goals with highest priority. Even though the health care system has been completely focused on the infected patients that are coming in large numbers, it could not prevent the mortalities that happened. Death toll has kept on increasing starting from February 2020. From the side of the government colossal,

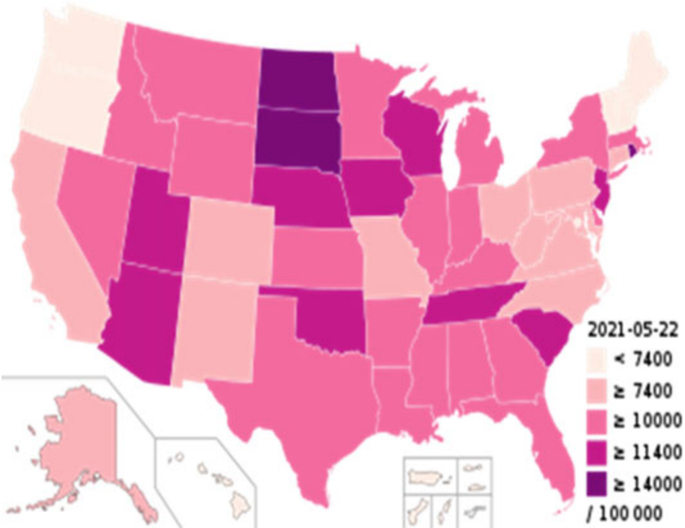


Fig. 3 COVID-19 cases per 100,000 people by state, as of May 1, 2020

amount of money has been used during the outbreak of the pandemic just to make situations under control. During the mid-March of 2020, a National Emergency has been declared and a bulky amount of medical equipment are purchased in order to fight back with the impacts the deadly virus on the public. There are cases of violence against the Asian Americans also as the great deal of unexpected changes has caused people to suffer mentally also.

All the fifty US states have been affected by the coronavirus by mid-April 2020 and all the territories have confirmed cases by November 2020. This is the first wave that has created confusion amidst disappointment. The second rise of the coronavirus infection has begun in June 2020 as many restrictions have been removed after the number of cases is controlled after the first wave. The daily positive cases are found to be more than 60,000 in the second wave. Once again, the restrictions have been imposed. The third rise in the infections has begun during the October 2020, where the number of cases has been approximately reaching 100,000 daily. The fourth rise has begun during March 2021 and is continuing at present also. Vaccinating the public has been started on December 14, 2020 but Vaccine hesitancy also is restricted the efforts of the government.

3.2 India

In India, the first case of the epidemic COVID-19 has been reported on January 30, 2020. Three students from Kerala who have returned form Wuhan are contracted to the disease. It has taken less than five months for the COVID-19 to spread to all the states and territories of India. After United States, the largest number of corona virus cases is in India only. Since the country is very large in size with the population of 134 million it is quite a challenge to control the uncertainties due to the pandemic. Figure 4 shows the cumulative positive cases for India. The country consists of 28 provinces and 8 Union Territories. The population densities of India are 424 person/km^2 [2–4] whereas the area is 3,287,590 km^2 [42].

Lockdown has been announced soon after the spread of the disease. End of March of 2020, the lockdown started. Half of the total country's cases are reported in only five cities. Mumbai, Delhi, Ahmedabad, Chennai and Thane. The recovery rate has been seen better from June 10 2020 but the peak first wave has come around the mid-September 2020, with over 90,000 cases per day. In January 2021, the first wave has waned with approximately 15,000 cases per day. In India, the reported number of cases is 29.3 million and the deadly virus has caused third highest number of fatalities in the world. The number of deaths as on March 31 2021, has been reported as 162,920.

The second wave has been started in March 2021. Delta (B.1.617.2) variant is primarily responsible for the second wave. The second wave of the deadly virus has exploded like never before. Almost every home has the patients affected with the infection of the said virus. There is a shortage of the hospital beds, oxygen cylinders and like this amidst many discrepancies and disappointments deaths at a very large

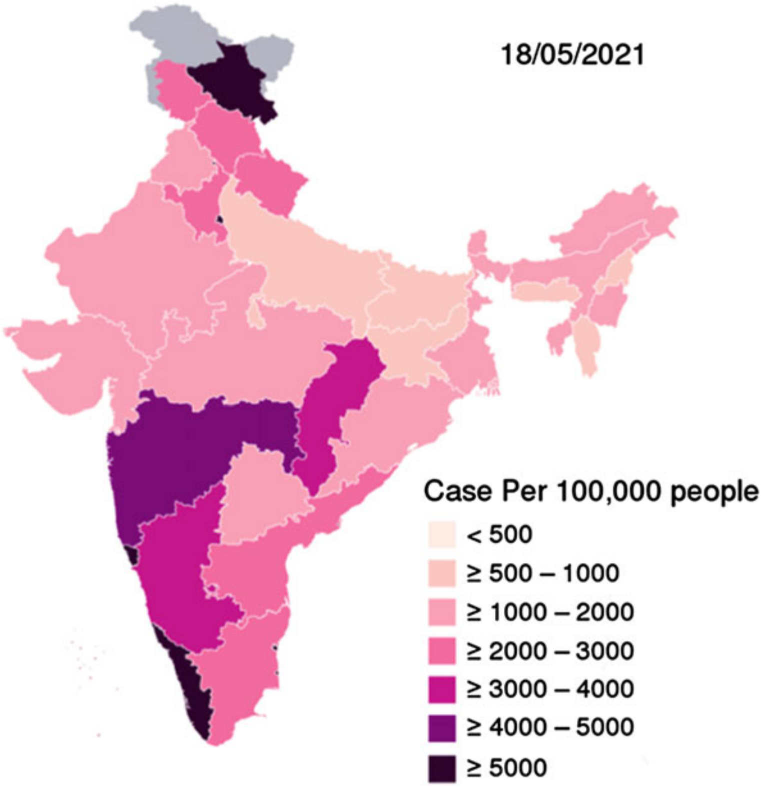


Fig. 4 COVID-19 cases in India

scale have hampered the development of the country as a whole. The impacts of the virus are adverse and beyond imagination. The very infectious delta variant is now spreading all around the world. In some countries, it has become a dominant variant. It has been found in 85 countries and is mutating at a very high speed. The future still remains a challenge. Vaccination program in India has been started on January16, 2021 and until March 31, 2021 millions of doses have been given to people. Many vaccines are being used in the country such as Covishield, Covaccine, Sputnik V.

3.3 United Kingdom (UK)

In UK, the total population is 68,207,116 whereas the population density is 279.98/km^2. The area of USA is 241,930 km^2. In late January 2020, the pandemic has reached within the bounds of UK. Figure 5 shows the cumulative positive cases for UK. The testing of the susceptible has begun in the early months of the year 2020 (February and March). A four-pronged strategy by government has been followed

Fig. 5 COVID-19 in UK

in UK: contain, delay, research, mitigate. In the end of March 2020, lockdown has been imposed in the country. Everything from schools to travel to large gatherings has been banned by the government. Mostly people have been told to self-isolate leaving the once who are having illness, they are hospitalized. Social distancing is a new normal during the spread of the pandemic. Even the police are given the rights to impose the laws which are then recently defined by the government. There have been 4 million cases confirmed and more than 128,191 fatalities in the country. Due to lockdown, people have gone into depression and suffered mentally also [43].

Due to the proper measures taken to curb the spread of the virus, the cases have gone down till June 2020; the exponential rise is getting flattened. By early September the country has started to retract the steps of lockdown, schools are reopened and as soon as the country has tried to return back to normal, suddenly there is an upsurge in the number of cases, depicted as the second wave there is commotion again. All the restrictions have been imposed back again. Stepwise restrictions are followed in many places during October 2020 while in November 2020 the country has been imposed

Table 1 Peaks/waves in different countries

Countries	Waves	Months
USA	3	May 2020, August 2020, January 2021
India	2	September 2020, May 2021
Brazil	5	August 2020, December 2020, January 2021, April 2021, June 2021
Russia	2	May 2020, January 2021
France	3	April 2020, November 2020, April 2021
UK	2	May 2020, January end/February 2021

the second lockdown. During Christmas there is a certain relaxation following which the country has gone for lockdown. The first country to have vaccination drive is UK only. In the early 2021, UK has the largest vaccination drive which is highest in Europe. Schools have been reopened in the month of March 2021, together with the quarantine rules. By June 2021, the delta variant has caused a third wave in UK. Table 1 shows the peaks of the active cases in different countries.

3.4 Russia

In Russia, the total population is about 145,912,025 whereas the population density is 9/km^2. The area of Russia is 17,098,242 km^2. The ongoing Pandemic in Russia is caused by the coronavirus 2019. The first case of the SARS-COV-2 hits the country on January 31, 2020. The borders have been tightened with China and the number of testing has been increased, these are the early measures taken at the time of the outbreak of the pandemic, during the month of March 2020, the infections spread from Italy causing the government to take the measures of lockdown, school shutting, borders are sealed, large gatherings and events are also cancelled till mid May 2020. [44]. Figure 6 shows the cumulative positive cases for Russia.

By the end of September 2020, the wave has reached the peak, every month saw an increase of million people, 2 million in November, 2020, 3 million in December 2020, 4 million in February 2021. During December 2020, the no of positive cases has reached to 3.2 million and the death toll has reached 100,000 during the end of March 2021. The difference between the number of deaths said by the government and the real figures are enormous, the number of fatality cases is greatly underestimated.

3.5 France

In France the total population is 65,426,176 whereas the population density is 119/km^2. The area of France is 551,695 km^2. On January 24 2020, the first case of the disease has been found out. The very first five cases are those persons who

Fig. 6 COVID-19 pandemic in Russia

have returned from China. The first COVID death outside Asia is in France itself where a Chinese tourist has died due to COVID pandemic on February 14. Between February 17 and February 24, 2020 there is a large gathering of almost 2500 people. Half of them contracted to the virus after which the horrors of the pandemic have begun. Figure 7 shows the cumulative positive cases for France. Strict measures are taken by the government authorities like banning of gatherings and schools and Universities closing, restaurants, cafes, cinemas followed by the compulsory home

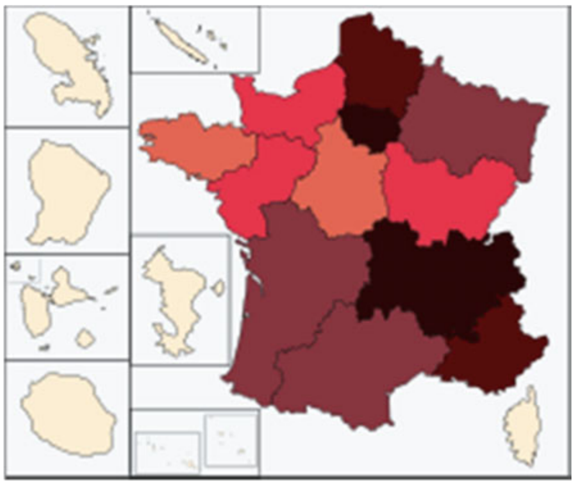


Fig. 7 COVID19 in France

lockdown for 15 days starting from March 17, 2020. The usage of face masks is made a compulsion and the lockdown is continued till May 11, 2020 [45].

In August 2020, again the same scenario has been seen to popup. There is an increase of number of infections. Consequently, France has to enter the second lockdown on October 28, 2020. 2.8 million people have got infected during the same time. The third lockdown has been imposed on March 31, 2021. It continues till April 3, 2021 where all the non-essential shops are closed down, all the domestic travel has been banned and a curfew has been imposed from 7 pm till 6 am.

3.6 Brazil

In Brazil the total population is 213,993,437 whereas the population density is 25/km^2. The SARS-COV-2 sets its foot on February 25, 2020. Figure 8 shows the cumulative positive cases for Brazil. By late March 2020 the disease spread throughout the country. On June 19, 2020 cases hit by one million and approximately 49,000 deaths have been reported [46].

During March 2020, Brazil has proclaimed a ban on the travellers who have come from outside. All the prevention measures have been taken to stop the very rapid explosion of coronaviruses infection. As on May21, 2021, 15 million cases are confirmed and the death toll has reached 425,000. Brazil has been repeatedly hit by the waves of coronavirus. Five peaks have been observed since last year. In Brazil, summer is the major season which lasts approximately the whole year round. It may

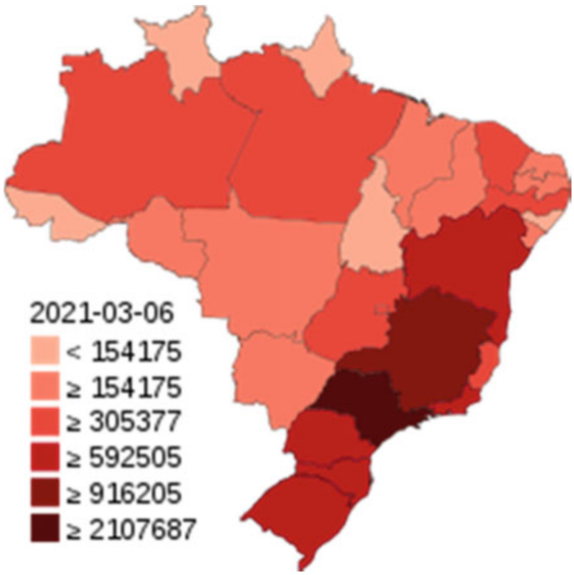


Fig. 8 Map of outbreak in Brazil

be the reason that the virus has got adjusted quickly to come back again and again causing great deal of commotion in the entire country.

3.7 Summary

Table 2 shows the population density, population, area, predominant variants of coronavirus in different countries. The uncertainty during the pandemic has a worse impact on the patterns of education, the economy and the politics as well. UK stands on number three, first and second being USA and India. Being toddlers in the understanding when would the epidemic end, the infection is of coronavirus is hitting the countries every now and then with its mutant variant. The type of consequences of the new variants is an unanswered question.

4 Experimental Results

To understand the behavior of the pandemic COVID-19 in six countries, a number of statistical tests has been considered. To see whether or not there exists any similarity among these, three statistical errors viz. *RMSE*, R^2 and χ^2, are considered. These errors are studied on the basis of number of positive cases, number of deceased, number of recovered cases, and total number of test cases [47], for the said 365 days.

This section has considered three types of cases (relative positive cases, relative recovered cases, relative deceased cases) of the six countries of India, USA, UK, Brazil, France and Russia. We have collected the data for 365 days starting from April 1, 2020. The relative positive cases, relative deceased cases, relative recovered cases are considered for our study. It analyses the behavior of pandemic COVID-19 across the six countries. On the pandemic, the information available are the total number of positive cases, total number of death cases, total number of recovered patients and total number of tests that are carried out daily. The behavior of pandemic is studied over the six countries using this set of data. Since the pandemic covered

Table 2 Different variants of six countries

Countries	Density	Population	Area	Waves	Prominent variants
India	424.00/km^2	1,393,409,038	3,287,590 km^2	2	Delta
USA	33.86/km^2	332,644,518	9,161,923 km^2	4	Alpha, beta, delta
Brazil	25.00/km^2	213,993,437	8,515,767 km^2	2	Alpha, delta
Russia	9.00/km^2	145,912,025	17,098,242 km^2	2	Alpha, beta, delta
France	119.00/km^2	65,426,176	551,695 km^2	3	Alpha, delta
UK	279.98/km^2	68,207,116	241,930 km^2	3	Alpha, delta

the entire countries by April 1, 2020, we have considered the data the period from April 1, 2020 to March 31, 2021; that means, our study is restricted for 365 days.

Figure 9 depicts the relative number of deceased cases for the six countries. The graph shows a blue curve which is the data. The x axis is the number of days while the y axis is the number of relative deceased cases. Each polynomial is represented by a color line segment. Purple color line segment is obtained by fitting the polynomial of degree 2 on the set of data and the green color line segment represents the polynomial of degree 3 while that of degree 4 on the dataset is represented by the blue color line segment and maroon for degree 5. Figure 10 depicts the graphs of the relative positive cases of six countries respectively for 365 days starting from April 1, 2020. Each figure also shows polynomial of degree 2, 3, 4 and 5 fitted on the set of data. In Fig. 11 the x-axis of the graph shows the number of days while the y-axis represents the number of relative recovered cases in the given days.

Tables 3 and 4 depict the coefficients of polynomials for the six countries of USA, India, UK, France, Brazil, Russia. Three different cases are relative recovered cases, relative deceased cases and relative positive cases. Tables 5 and 6 depict the values of the RMSE, R^2 and $\boldsymbol{\chi^2}$ of the six countries.

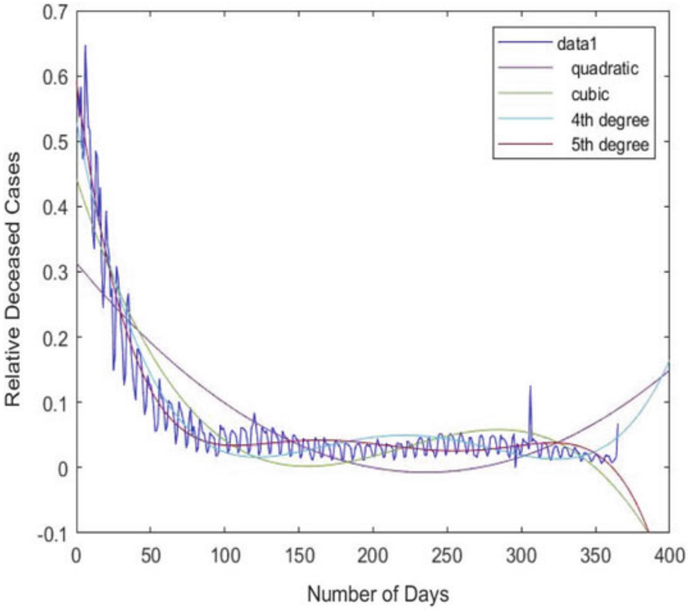
The values shown are for the quadratic, cubic, fourth and the fifth-degree polynomial fit curve. The values are calculated once the polynomial curves are made from the given data set. Lower the value of RMSE the better the results and lager the value of R^2 better is the polynomial fit. Once these data are fitted in the polynomial it is given as an input to the SIR model.

4.1 Comparative Study

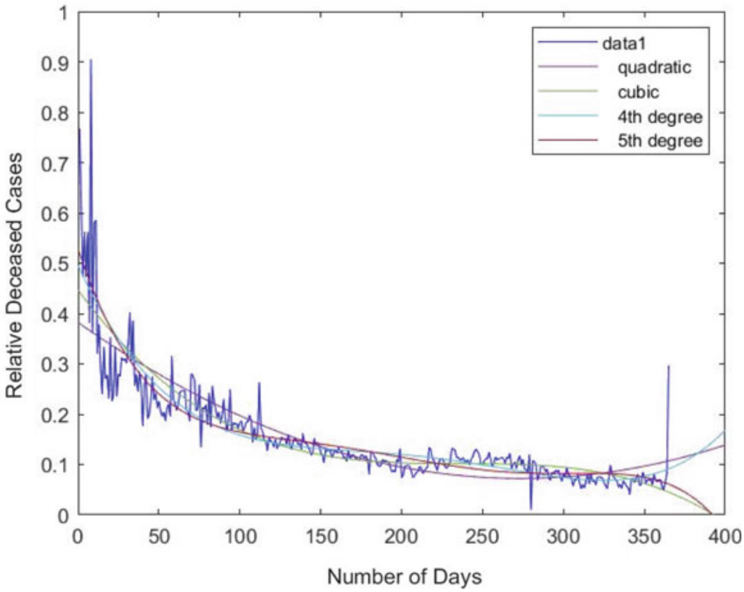
In this section, different parameters for six different countries (USA, India, Brazil, France, UK, Russia) are calculated. A year is divided into three equal parts, each consisting of four months. The parameters tell us the current scenario of COVID-19 in the six most affected countries of the world. The parameter Beta is the rate of infection, Alpha depicts the recovery rate and R_0 tells number of secondary cases caused by a single infected case where as m is the slope or the difference between transmission rate and the recovery rate and s is the fraction of total susceptible. Tables 7, 8 and 9 along with Figure provide different parameters and graphs of the same of the six countries, each of four months.

It is clear from Table 7 that the highest rate of infection is in India while that of U.K is the lowest in the Ist Part of the year, i.e., from April to July 2020. The recovery rate for the Ist Part of the year is the highest in France and it is lowest in USA. The basic reproduction rate is the highest in Russia and France stands the lowest in R_0.

The recovery rate (Alpha value) of the six countries is shown in Fig. 12 which compares the value of recovery rate for six countries for three different parts of the year. It can be seen that for different countries, no trend is being followed by the recovery rate. For some countries, it is always on the higher side, for another set

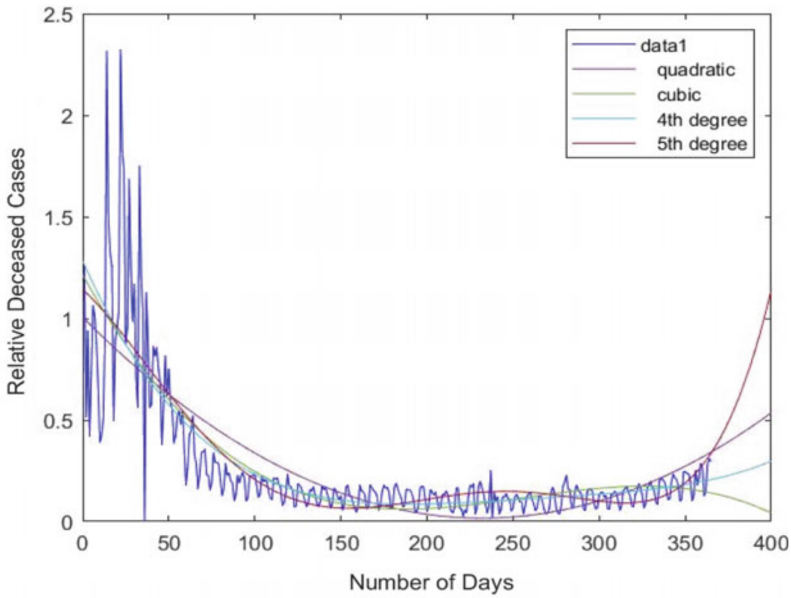


(a) Relative Deceased Cases against Number of Days in USA

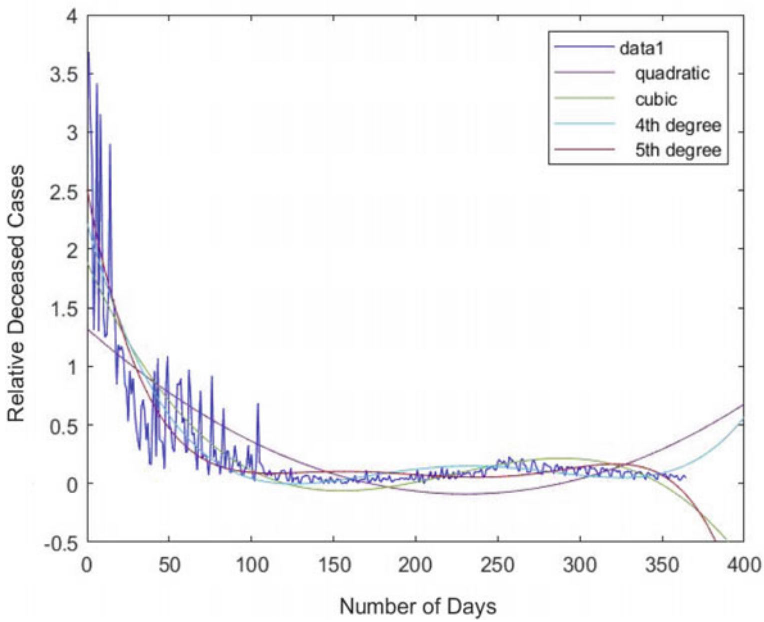


(b) Relative Deceased Cases against Number of Days in India

Fig. 9 Relative deceased cases against number of days in six countries

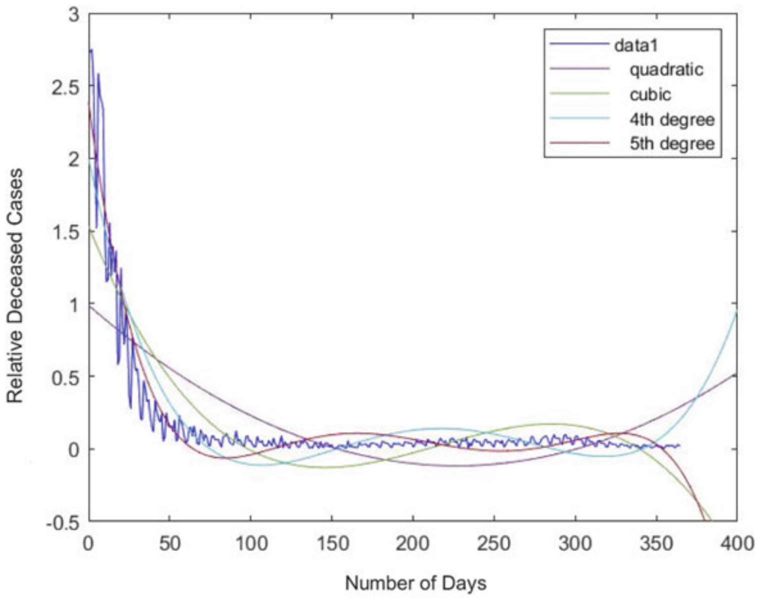


(c) Relative Deceased Cases against Number of Days in Brazil

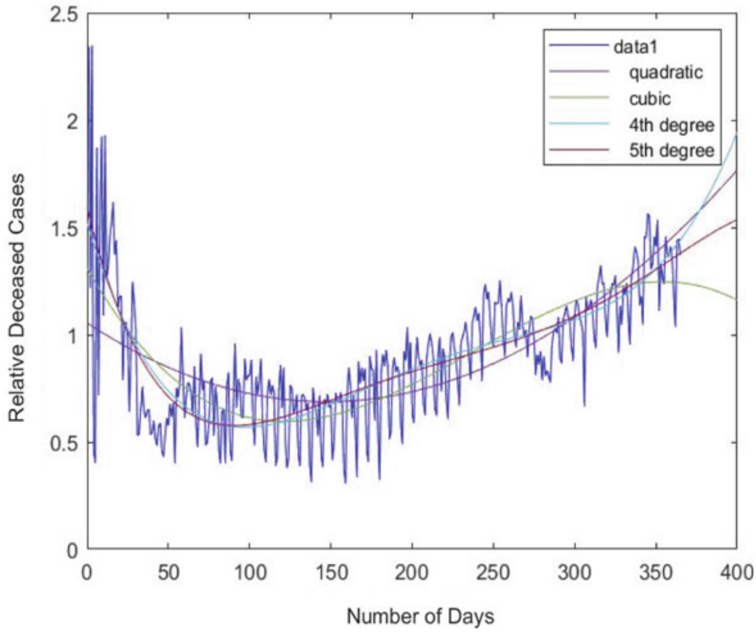


(d) Relative Deceased Cases against Number of Days in France

Fig. 9 (continued)

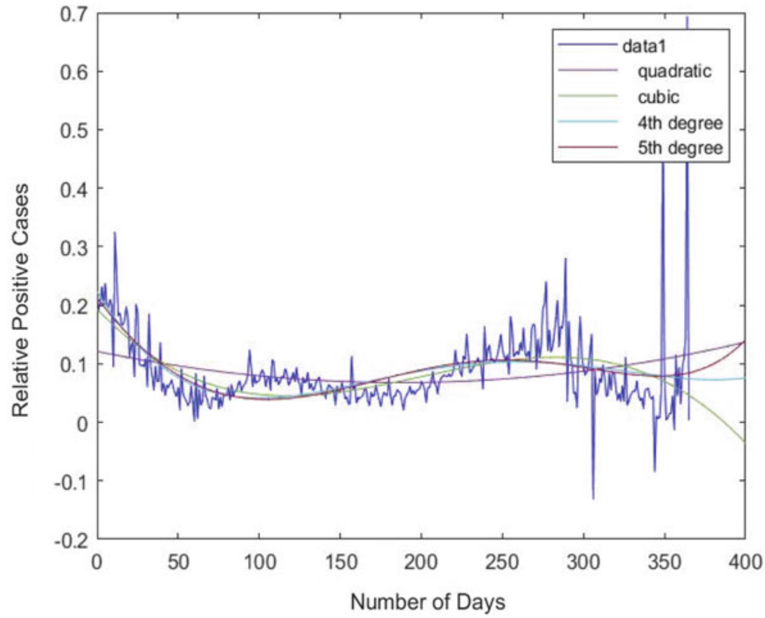


(e) Relative Deceased Cases against Number of Days in UK

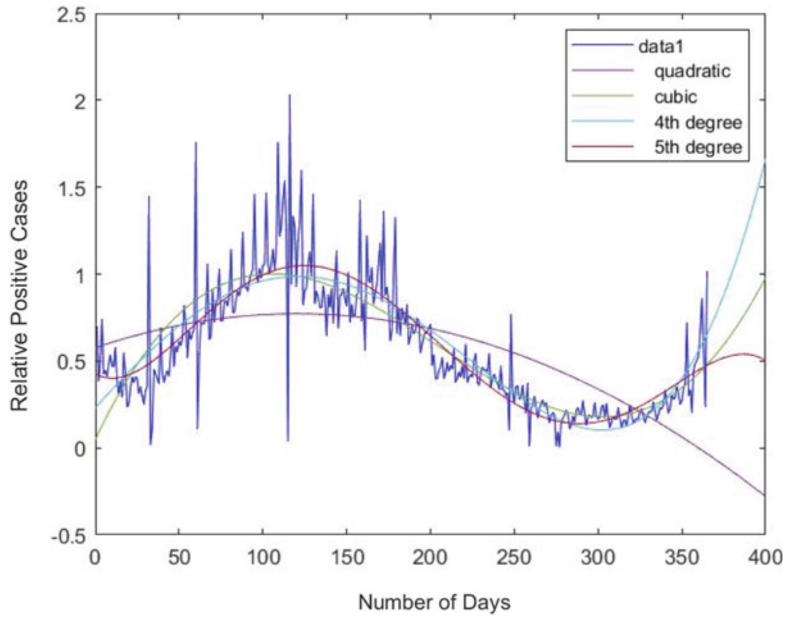


(f) Relative Deceased Cases against Number of Days in Russia

Fig. 9 (continued)

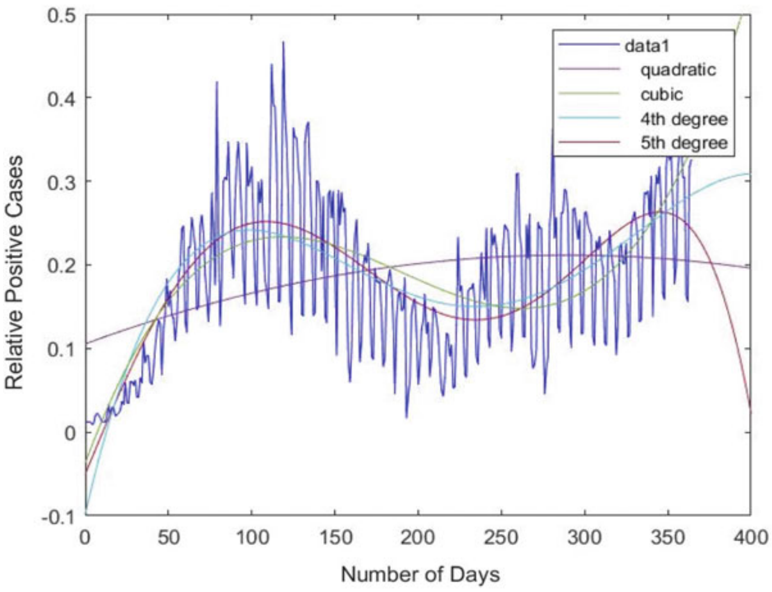


(a) Relative Positive Cases against Number of Days in USA

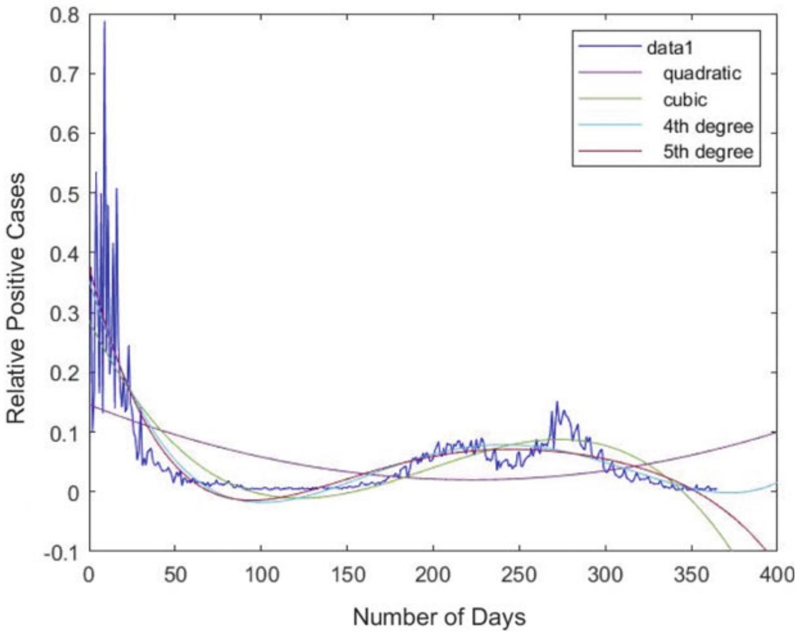


(b) Relative Positive Cases against Number of Days in India

Fig. 10 Relative positive cases against number of days in five countries

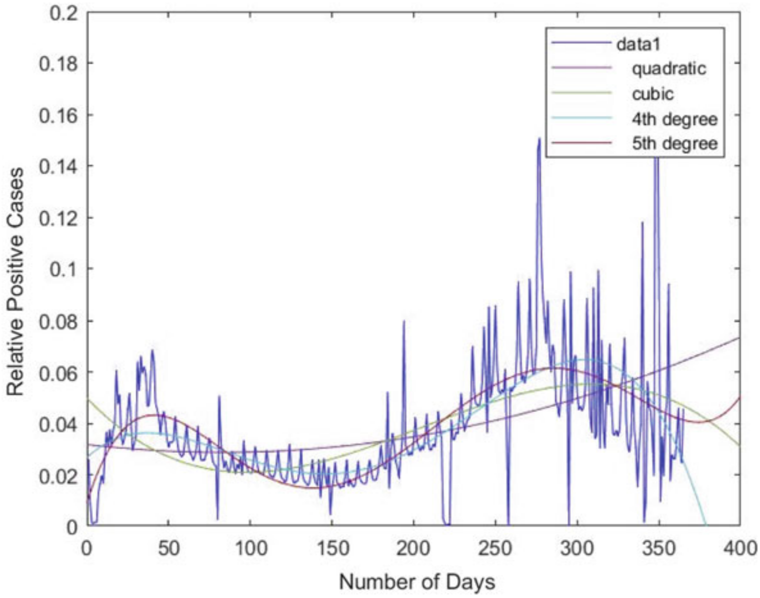


(c) Relative Positive Cases against Number of Days in Brazil



(d) Relative Positive Cases against Number of Days in UK

Fig. 10 (continued)



(e) Relative Positive Cases against Number of Days in Russia

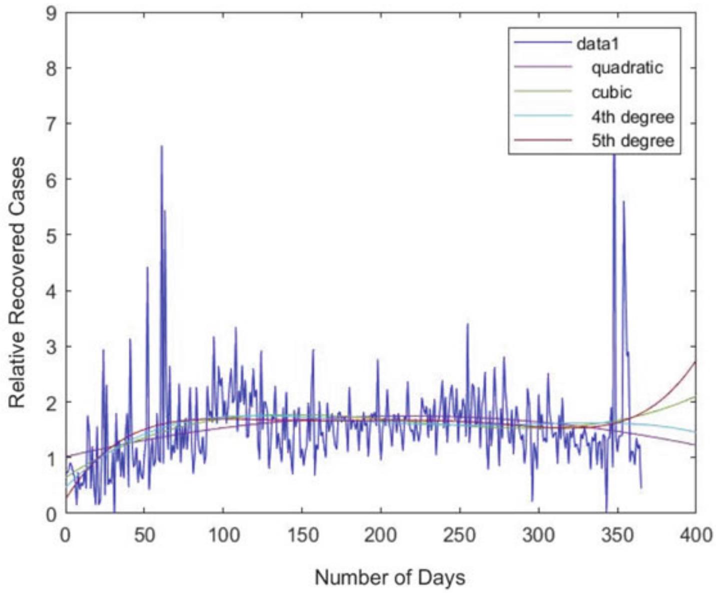
Fig. 10 (continued)

it is low. Depending upon the immunity and the speed with which the infection is spreading, the graph has calculated the different values of Alpha.

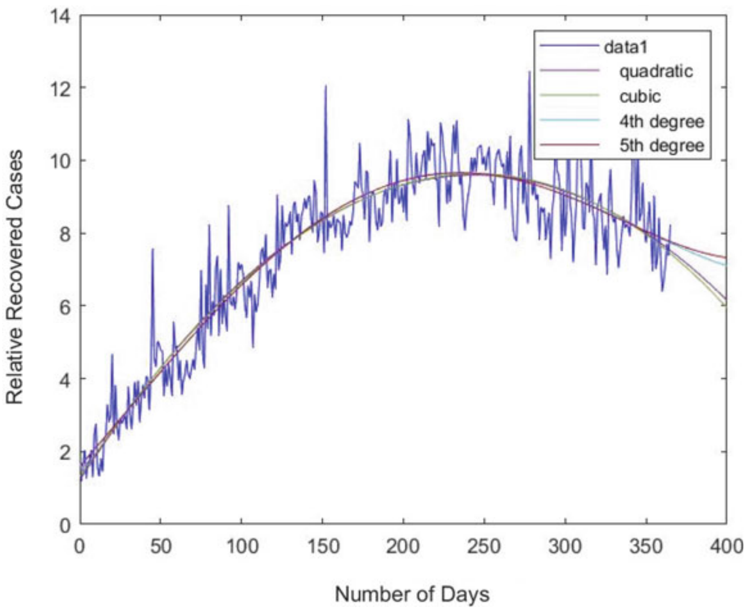
Values in I part of the year (April 2020–July 2020)

In the IInd Part of the year, once again the rate of infection is the highest in USA and the lowest in Russia. Brazil showed much improvement in controlling the rate of infection compared to beta of France which increased from Ist Part of the year to IInd Part of the year. Beta values of USA, India, Brazil have decreased compared to the Ist Part of the year while it has increased for France, UK and Russia. India remains at number one in the average number of secondary infections caused by an infected individual while UK has recorded the lowest number according to the graph. Comparing the countries in the IInd Part of the year, the highest recovery rate is in USA while the lowest is in Russia.

The different parameters of six countries are shown for the IInd Part of the year in Table 8. The IInd Part of the year shows the value of the basic reproduction number is the highest in France and the lowest in Brazil. The infection rate is the highest in India and the lowest in USA while the recovery rate of the IInd Part of the year is the highest in India again and the lowest in UK.

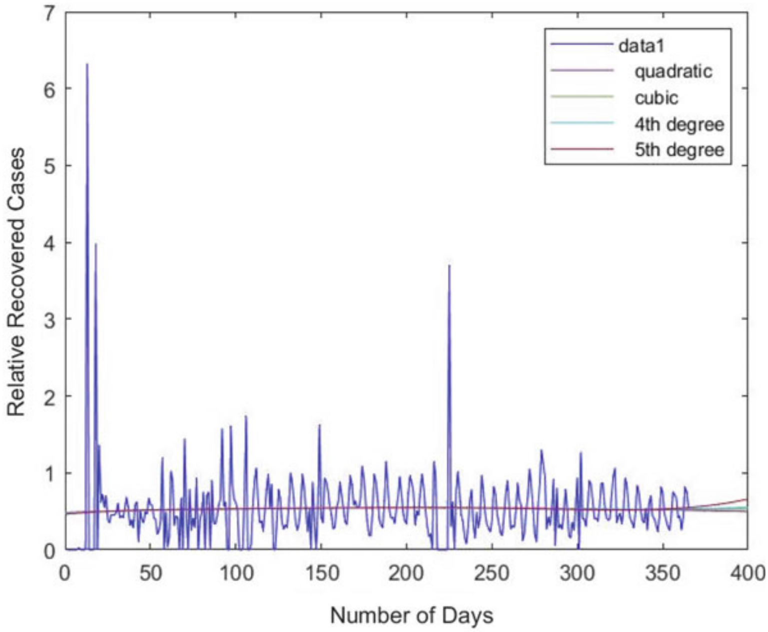


(a) Relative Recovered Cases against Number of Days in USA

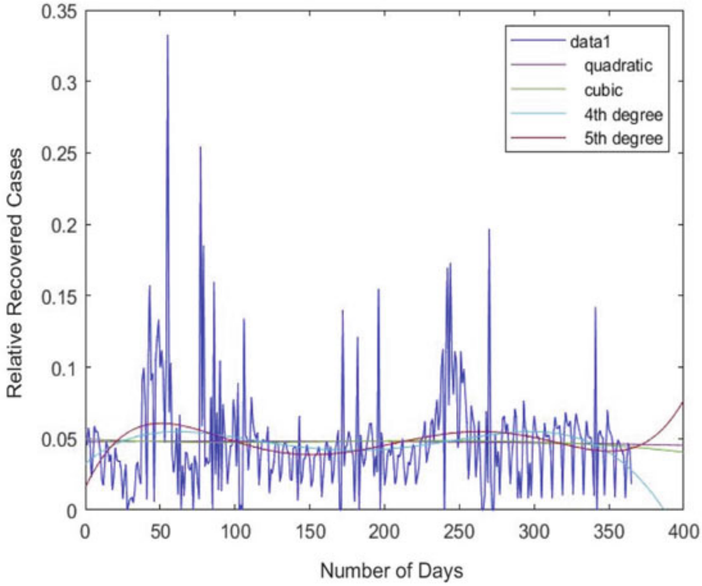


(b) Relative Recovered Cases against Number of Days in India

Fig. 11 Relative recovered cases against number of days in six countries

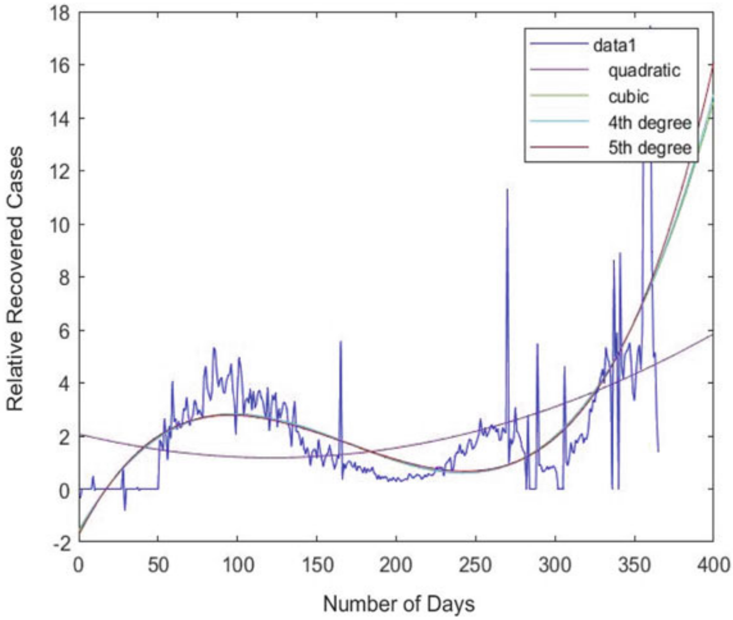


(c) Relative Recovered Cases against Number of Days in Brazil

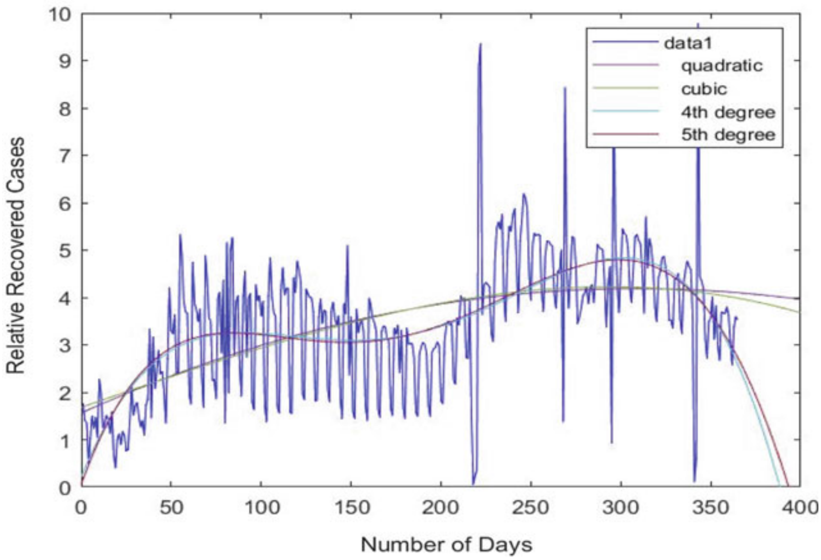


(d) Relative Recovered Cases against Number of Days in France

Fig. 11 (continued)



(e) Relative Recovered Cases against Number of Days in UK



(f) Relative Recovered Cases against Number of Days in Russia

Fig. 11 (continued)

Table 3 Coefficients of polynomials for different countries of India, USA and UK

Case	Country	Polynomial	a_0	a_1	a_2	a_3	a_4	a_5
Relative positive cases	UK	Quadratic	$2.93e^{-11}$	$-1.128\ e^{-8}$	0.15			
		Cubic	$-5.71\ e^{-13}$	$3.389\ e^{-10}$	$-5.725\ e^{-8}$	0.29		
		4th degree	$2.56\ e^{-15}$	$-2.452\ e^{-12}$	$7.818\ e^{-10}$	$-9.339\ e^{-8}$	0.35	
		5th degree	$-8.769\ e^{-18}$	$1.059\ e^{-14}$	$-5.064\ e^{-12}$	$-1.141\ e^{-9}$	$-1.123\ e^{-7}$	0.38
	Russia	Quadratic	4.47	−7.41	0.03			
		cubic	−7.26	4.44	0	0.05		
		4th degree	−8.81	5.72	−1.08	0	0.03	
		5th degree	6.65	−6.88	2.52	−3.76	0	0.01
	USA	Quadratic	$1.52e^{-6}$	0	0.12			
		Cubic	$-2.93\ e^{-8}$	$1.76\ e^{-5}$	0	0.19		
		4th degree	$1.15\ e^{-10}$	$-1.13\ e^{-7}$	$3.74\ e^{-5}$	0	0.22	
		5th degree	$4.07\ e^{-13}$	$-2.58\ e^{-10}$	$7.94\ e^{-9}$	$2.07\ e^{-5}$	0	0.21
	India	Quadratic	$-1.35\ e^{-6}$	0	0.06			
		Cubic	$2.14\ e^{-8}$	$-1.13\ e^{-5}$	0	0		
		4th degree	$7.08\ e^{-11}$	$-3.04\ e^{-8}$	$-9.08\ e^{-7}$	0	0.02	
		5th degree	$-7.26\ e^{-13}$	$7.35\ e^{-10}$	$-2.47\ e^{-7}$	$2.88\ e^{-5}$	0	0.04
	Brazil	Quadratic	$-1.27\ e^{-6}$	0.001	0.11			
		Cubic	$5.77\ e^{-8}$	$-3.29\ e^{-5}$	0.01	−0.04		
		4th degree	$-2.34\ e^{-10}$	$2.29\ e^{-7}$	$-7.33\ e^{-5}$	.001	−0.10	
		5th degree	$-1.78\ e^{-12}$	$1.40\ e^{-9}$	$-3.02\ e^{-7}$	$-1.80\ e^{-7}$	0.01	−0.05

(continued)

Table 3 (continued)

Case	Country	Polynomial	a_0	a_1	a_2	a_3	a_4	a_5
Relative deceased cases	UK	Quadratic	$2.145\ e^{-5}$	−0.001	0.99			
		Cubic	$-2.206\ e^{-7}$	0.001	−0.028	1.53		
		4th degree	$1.789\ e^{-9}$	$-1.530\ e^{-6}$	0.001	−0.053	2.0	
		5th degree	$-1.446\ e^{-11}$	$1.502\ e^{-8}$	$-5.837\ e^{-6}$	0.001	−0.084	2.39
	USA	Quadratic	$5.781\ e^{-6}$	−0.003	0.31			
		Cubic	$-5.236\ e^{-8}$	$3.453\ e^{-5}$	−0.007	0.44		
		4th degree	$3.345\ e^{-10}$	$-2.972\ e^{-7}$	$9.210\ e^{-5}$	−0.012	0.53	
		5th degree	$-2.304\ e^{-12}$	$2.443\ e^{-9}$	$-9.835\ e^{-7}$	0.001	−0.017	0.59
	India	Quadratic	$4.16\ e^{-8}$	$-2.30\ e^{-5}$	0			
		Cubic	$-2.26\ e^{-10}$	$1.65\ e^{-7}$	$-4.12\ e^{-5}$	0		
		4th degree	$1.43\ e^{-12}$	$-1.28\ e^{-9}$	$4.13\ e^{-7}$	$-6.13\ e^{-5}$	0	
		5th degree	$-1.08\ e^{-14}$	$1.13\ e^{-11}$	$-4.48\ e^{-9}$	$8.53\ e^{-7}$	$-8.45\ e^{-5}$	0
Relative recovered cases	UK	Quadratic	$6.225\ e^{-5}$	−0.016	0.02			
		Cubic	$1.518\ e^{-6}$	−0.001	0.107	−0.02		
		4th degree	$3.780\ e^{-10}$	$1.242\ e^{-6}$	−0.001	0.101	−0.02	
		5th degree	$6.831\ e^{-12}$	$-5.872\ e^{-9}$	$3.276\ e^{-6}$	−0.001	0.116	−0.02
	USA	Quadratic	−1.56	0	1.01			
		Cubic	1.49	−9.76	0.02	0.65		
		4th degree	−6.72	6.41	0	0.03	0.47	
		5th degree	8.13	−8.11	3.06	0	0.05	0.25

(continued)

Table 3 (continued)

Case	Country	Polynomial	a_0	a_1	a_2	a_3	a_4	a_5
	India	Quadratic	0	0.07	1.22			
		Cubic	$-3.50e^{-8}$	0	0.07	1.31		
		4th degree	$1.19\ e^{-9}$	$-9.06\ e^{-7}$	$8.33\ e^{-5}$	0.05	1.62	
		5th degree	$1.43\ e^{-12}$	$-1.17\ e^{-10}$	$-4.80\ e^{-7}$	$2.48\ e^{-5}$	0.05	1.58

Table 4 Coefficients of polynomials for different countries of Brazil, Russia and France

Case	Country	Polynomial	a_0	a_1	a_2	a_3	a_4	a_5
Relative deceased cases	France	Quadratic	$2.66e^{-5}$	−0.01	1.32			
		Cubic	$-2.29\ e^{-7}$	0	−0.03	1.89		
		4th degree	$1.27\ e^{-9}$	$-1.16\ e^{-6}$	0	−0.05	2.22	
		5th degree	$1.08\ e^{-11}$	$1.11\ e^{-8}$	$-4.37\ e^{-6}$	0	−0.07	2.51
	Russia	Quadratic	$1.694\ e^{-6}$	−0.001	0.10			
		Cubic	$-1.034\ e^{-8}$	$7.373\ e^{-6}$	−0.001	0.13		
		4th degree	$7.999\ e^{-11}$	$-6.890\ e^{-8}$	$2.116\ e^{-5}$	−0.003	0.15	
		5th degree	$-2.53\ e^{-13}$	$3.203\ e^{-10}$	$-1.471\ e^{-6}$	$3.192\ e^{-5}$	−0.003	0.16
	Brazil	Quadratic	$1.84\ e^{-5}$	−0.01	1.01			
		Cubic	$-8.39\ e^{-8}$	$6.44\ e^{-5}$	−0.02	1.21		
		4th degree	$2.64\ e^{-10}$	$-2.77\ e^{-7}$	−0.001	−0.02	1.28	
		5^{t}h degree	$5.27\ e^{-12}$	$-4.55e^{-9}$	$1.29\ e^{-6}$	−0.0001	−0.01	1.14
Relative recovered cases	France	Quadratic	$2.66\ e^{-7}$	0	0.01			
		Cubic	$-2.30\ e^{-9}$	$1.52\ e^{-6}$	0	0.02		
		4th degree	$1.27\ e^{-11}$	$-1.11\ e^{-8}$	$3.72\ e^{-6}$	0	0.02	
		5th degree	$-1.08\ e^{-13}$	$1.11\ e^{-10}$	$-4.37\ e^{-8}$	$8.13\ e^{-6}$	0	0.02
	Russia	Quadratic	$-2.76\ e^{-5}$	0.02	1.56			
		Cubic	$-4.81\ e^{-8}$	$-1.17\ e^{-6}$	0.01	1.68		
		4th degree	$-5.64\ e^{-9}$	$4.08\ e^{-6}$	0	0.09	0.21	

(continued)

Table 4 (continued)

Case	Country	Polynomial	a_0	a_1	a_2	a_3	a_4	a_5
		5th degree	$5.73\ e^{-12}$	$-1.09\ e^{-8}$	$5.79\ e^{-6}$	0	0.10	0.05
	Brazil	Quadratic	$-1.34\ e^{-6}$	0.001	0.49			
		Cubic	$5.57\ e^{-9}$	$-4.40\ e^{-6}$	0.001	0.47		
		4th degree	$2.39\ e^{-11}$	$-1.19\ e^{-8}$	$-2.78\ e^{-7}$	0.001	0.48	
		5th degree	$6.77\ e^{-13}$	$-5.96\ e^{-10}$	$1.90\ e^{-7}$	$-2.80\ e^{-5}$	0.002	

Table 5 RMSE, R^2 and χ^2 for USA, Brazil and India

Case	Country	Polynomial	RMSE	R^2	χ^2
Relative positive cases	USA	Quadratic	1.2211	0.0534	14.1590
		Cubic	1.1073	0.2216	17.6048
		4th degree	1.1097	0.2425	13.9746
		5th degree	1.0900	0.2458	13.5174
	Brazil	Quadratic	1.7260	0.1056	16.9490
		Cubic	1.3970	0.4136	10.3380
		4th degree	1.3450	0.4564	09.2280
		5th degree	1.3190	0.4774	08.9400
	India	Quadratic	0.5427	0.3795	13.1563
		Cubic	0.3909	0.6780	03.3540
		4th degree	0.3738	0.7055	02.2849
		5th degree	0.3581	0.7299	01.9976
Relative deceased	USA	Quadratic	1.2370	0.6370	28.6715
		Cubic	0.8280	0.8380	21.5605
		4th degree	0.6280	0.9070	06.5000
		5th degree	0.5270	0.9340	02.9739
	Brazil	Quadratic	4.0030	0.6130	58.6410
		Cubic	3.7220	0.6650	25.3350
		4th degree	3.6970	0.6700	21.0690
		5th degree	3.6140	0.6840	22.6700
	India	Quadratic	0.0150	0.5798	0.0917
		Cubic	0.0144	0.6093	0.0909
		4th degree	0.0142	0.6193	0.0873
		5th degree	0.0141	0.6241	0.0931
Relative recovered	USA	Quadratic	15.0100	0.0557	155.8301
		Cubic	14.7800	0.0845	142.7590
		4th degree	14.7400	0.0895	141.7840
		5th degree	14.6900	0.0955	139.8890
	Brazil	Quadratic	9.6940	0.0010	183.1410
		Cubic	9.6930	0.0010	184.8410
		4th degree	9.6930	0.0010	184.3670
		5th degree	09.6920	0.0010	184.7580
	India	Quadratic	16.7400	0.8715	40.7939
		Cubic	16.7300	0.8717	40.5237
		4th degree	16.6200	0.8734	40.2154
		5th degree	16.6200	0.8734	40.1602

Table 6 RMSE, R^2 and χ^2 for Russia, UK, France

Case	Country	Polynomial	RMSE	R^2	χ^2
	UK	Quadratic	1.4240	0.1630	29.8600
		Cubic	1.0110	0.5781	69.3739
		4th degree	9.2210	0.6491	23.9506
		5th degree	9.1290	0.6560	51.4326
	Russia	Quadratic	0.4286	0.1771	4.0854
		Cubic	0.4092	0.2500	3.6575
		4th degree	0.3837	0.3406	3.2122
		5th degree	0.3712	0.3828	3.0197
Relative deceased	France	Quadratic	6.4300	0.5521	202.3048
		Cubic	5.0170	0.7273	83.3179
		4th degree	4.5760	0.7732	56.8438
		5th degree	4.2900	0.8007	400.3171
	UK	Quadratic	5.8520	0.4746	58.4880
		Cubic	4.3870	0.7074	42.3198
		4th degree	3.3020	0.8327	24.0224
		5th degree	2.5140	0.9030	31.3106
	Russia	Quadratic	0.4470	0.4479	2.2054
		Cubic	0.4087	0.5383	1.7635
		4th degree	0.3873	0.5854	1.5936
		5th degree	0.3855	0.5892	1.5665
Relative recovered	France	Quadratic	0.0643	0.5521	94.7581
		Cubic	0.0502	0.7273	0.6593
		4th degree	0.0458	0.7732	87.1453
		5th degree	0.0429	0.8007	2.4662
	UK	Quadratic	43.1200	0.1591	62.3700
		Cubic	33.8900	0.4805	37.6237
		4th degree	33.88	0.4807	6.7785
		5th degree	33.87	0.4811	181.4085
	Russia	Quadratic	24.4000	0.2715	170.5692
		Cubic	24.3825	0.2724	171.6270
		4th degree	22.6200	0.3738	155.9504
		5th degree	22.6041	0.3747	168.5115

*Test data is not available in Our World in Data Total COVID−19 tests (http://www.ourworldindata.org)

Table 7 Parameters for I part of the year

Numbering	Country	Beta	m	Alpha	R_0	s
X1	USA	0.028789	0.016085	0.016085	1.789838	0.558710
X2	India	0.090292	0.039697	0.050595	1.784597	0.560351
X3	Brazil	0.081628	0.028335	0.053293	1.531671	0.652882
X4	France	0.040008	−0.016730	0.056738	0.705130	1.418178
X5	UK	0.020190	−0.003047	0.023238	0.868865	1.150926
X6	Russia	0.052377	0.024813	0.027564	1.900180	0.526266

Table 8 Parameters for IInd part of the year

Numbering	Country	Beta	m	Alpha	R_0	s
X1	USA	0.021094	0.004910	0.016184	1.303414	0.767216
X2	India	0.087290	−0.003081	0.090370	0.965912	1.035291
X3	Brazil	0.051264	−0.006157	0.057421	0.892776	1.120101
X4	France	0.072561	0.030447	0.042114	1.722965	0.580395
X5	UK	0.046789	0.035169	0.011629	4.024239	0.248494
X6	Russia	0.043153	0.010087	0.033067	1.305038	0.766261

Table 9 Parameters for IIIrd part of the year

Numbering	Countries	Beta	m	Alpha	R_0	s
X1	USA	0.018272	0.001470	0.016802	1.087496	0.9195440
X2	India	0.088344	−0.006967	0.955311	0.926905	1.078859
X3	Brazil	0.061002	0.005037	0.055965	1.090010	0.917423
X4	France	0.045608	0.006467	0.039141	1.652220	0.858206
X5	UK	0.025227	−0.003773	0.029000	0.869894	1.149565
X6	Russia	0.040165	−0.005396	0.045562	0.881559	1.134354

Values in IInd Part of the year (August 2020–November 2020)

Figure 13 shows the values of Basic Reproduction Number that is the number of cases which are infected by an infected individual. From the graph it is clear that the countries of USA, Russia and India have basic reproductive rate on the lower side as the time increases. But the other countries do not follow the same trend.

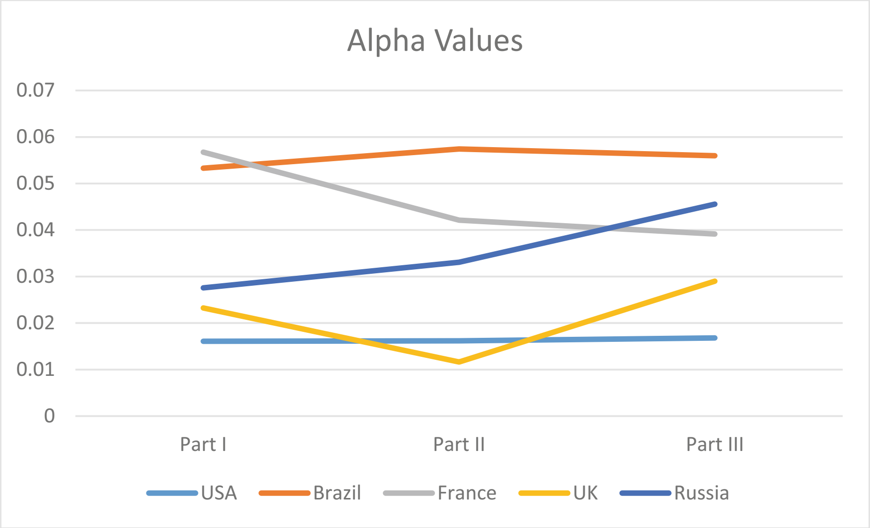


Fig. 12 AAlpha values for all the three parts of the year of the five countries viz. USA, Brazil, France, UK and Russia. Note that plot of India is not shown because of high variation which leads the problem of graph readability

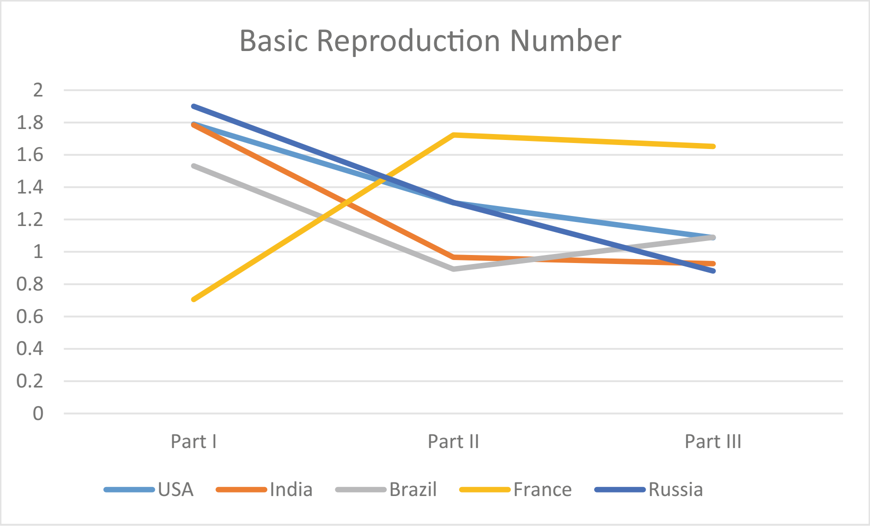


Fig. 13 Basic Reproduction Number for all the three parts of the year of the five countries viz. USA, India, Brazil, France and Russia. Note that plot of UK is not shown because of high variation which leads the problem of graph readability

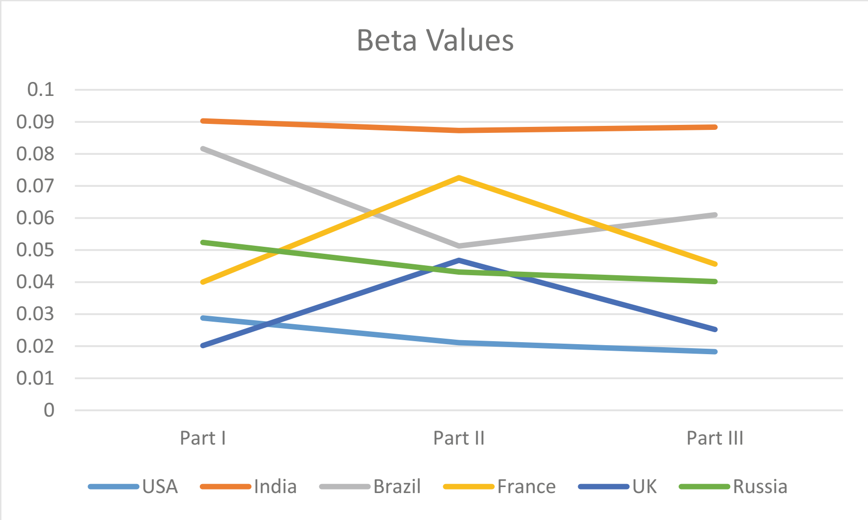


Fig. 14 Beta values for all three parts of the year of the six countries

Values in IIIrd Part of the year (December 2020–March 2021)

Table 9 shows the parametric values of different countries for the IIIrd Part of the year. The IIIrd Part of the year begins from the month of December 2020 till March 2021. The infection rate as well as the recovery rate for India and USA became the highest and the lowest respectively in the IIIrd Part of the year i.e., in the months of December 2020 to March 2021. UKs Basic Reproduction Number reached the lowest while France number reached the highest.

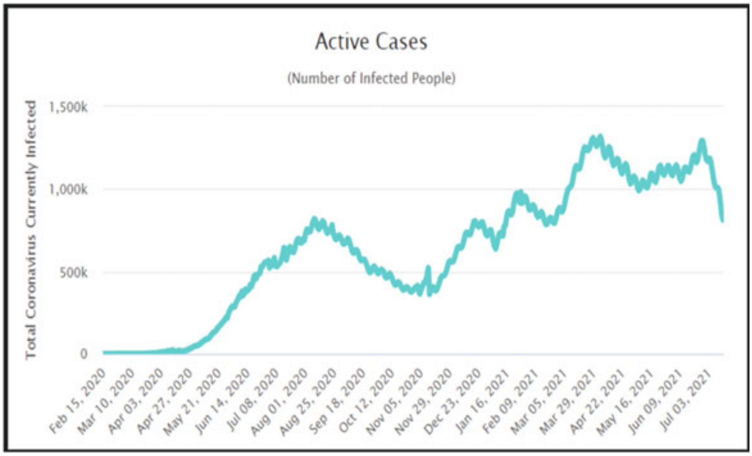
Figure 14 shows the rate of infection which is spreading in these six countries for individual three parts of the year. For Russia, the rate of infection is seen to be the highest in the Ist Part of the year but has decreased in the IInd Part of the year and still has come to a lower value in the IIIrd Part of the year. In the rest of the countries, the infection rate has not followed any order.

4.2 Next Peak Prediction

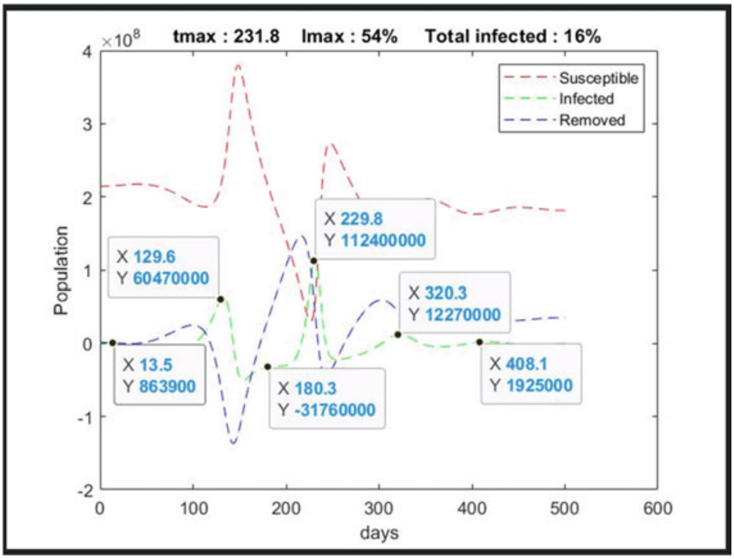
The predicted peaks for all the three countries are shown after July, 2020. The same can be done for other countries too. This prediction has been done based on the data observed up to 31st March 2021. However, these predictions may not be appropriate if one considers the successfulness of vaccination.

Brazil

It can be seen from Fig. 15a (taken from worldometer) there are 5 peaks in the active cases since April 2020. The peaks are in July end/August starting 2020, December



(a) Active Cases in Brazil (Worldometer)



(b) PG-SIR Model of Brazil

Fig. 15 Comparison of true peaks of Brazil

2020, January 2021, March end/Starting April 2021 and June end 2021. The PG-SIR model could predict all the five peaks from the data of first four months starting from April 1, 2020 to July 31, 2020. For Brazil, the 4th degree fit is taken for relative deceased cases, the quadratic fit is taken for relative recovered cases and the 5th degree fit has been considered for relative positive cases.

Table 10 Calculation of the predicted values of the next peak for Brazil

Peak	Calculation from Graph	Month
1	July (120 days) + 13 days	August, 2020
2	July (120 days) + 130 days	December, 2020
3	July (120 days) + 180 days	January, 2021
4	July (120 days) + 230 days	March, 2021
5	July (120 days) + 320 days	June, 2021

Table 11 Comparison of SIR and PG-SIR model for Brazil

Brazil		Beta	Slope	Alpha	R_0Basic reproduction number	s_0
1st part of the year	SIR	0.08163	0.02833	0.05329	1.53167	0.65288
	PG−SIR	−0.08929	0.03044	−0.00972	0.74575	1.01706
2nd part of the year	SIR	0.05126	−0.00616	0.05742	0.89278	1.12010
	PG−SIR	0.039483	−0.004629	0.04411	0.89507	1.11724
3rd part of the year	SIR	0.061002	0.005037	0.055965	1.090010	0.91742
	PG−SIR	0.07391	0.013373	0.06053	1.22092	0.81905

The next peak after June, 2021(the sixth peak), is predicted to be 408 days ahead of July 31, 2020 i.e., in mid-August, 2021. Results were calculated on the basis of the data available. The parameters of the SIR model and the PG-SIR model are shown in Table 10.

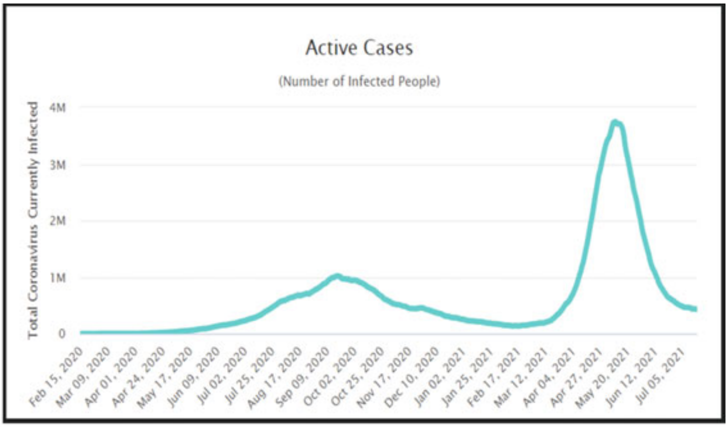
India

It can be seen from Fig. 16a (taken from worldometer) that there are 2 peaks in the active cases since April 2020. The peaks are in September 2020 and May 2021. The PG-SIR model can find the peaks from the data. The 4th degree fit has been taken for relatively deceased cases while for the relative positive and relative recovered cases 5th degree fit has been chosen as it has maximum correlation. 41% of the total population of India are the applicants which are having less than 18 years of age and those have not been vaccinated. Therefore, it is assumed that the third wave may hit the children the most.

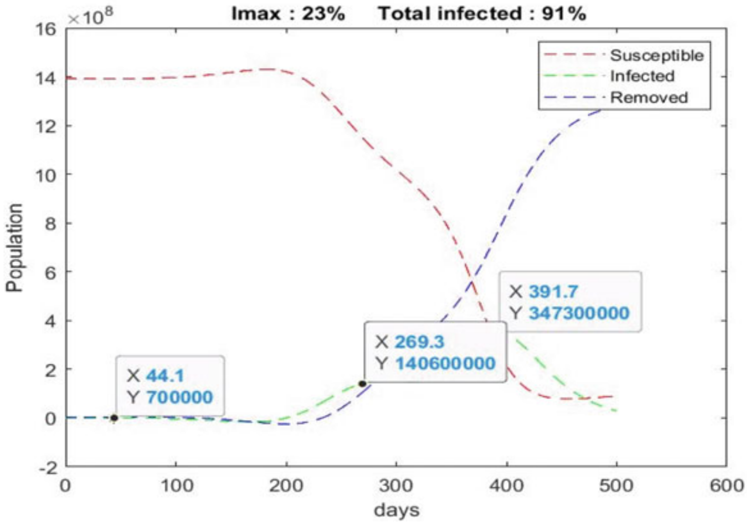
As India has a huge population, the peaks that have come actually and the predicted peaks have some variations. In May 2021, the cases for the next peak have been increasing exponentially. The parameters of the SIR model and the PG-SIR model are shown in Table 12.

France

In France, there are three peaks in total as shown in the worldometer diagram of the active cases. The first one is in April 2020, the second in November 2020 and the third is in April 2021. The data of the 1 year has been fed into the program and based



(a) Active Cases in India (Worldometer)



(b) PG SIR Model of India

Fig. 16 Comparison of true peaks of India

Table 12 Calculation of the predicted values of the next peak In India

Peak	Calculation from graph	Month
1	July (125 days) + 44 days	September, 2020
2	July (125 days) + 270 days	May, 2021
3	July (125 days) + 519 days	September, 2021

Table 13 Comparison of SIR and PGSIR model in India

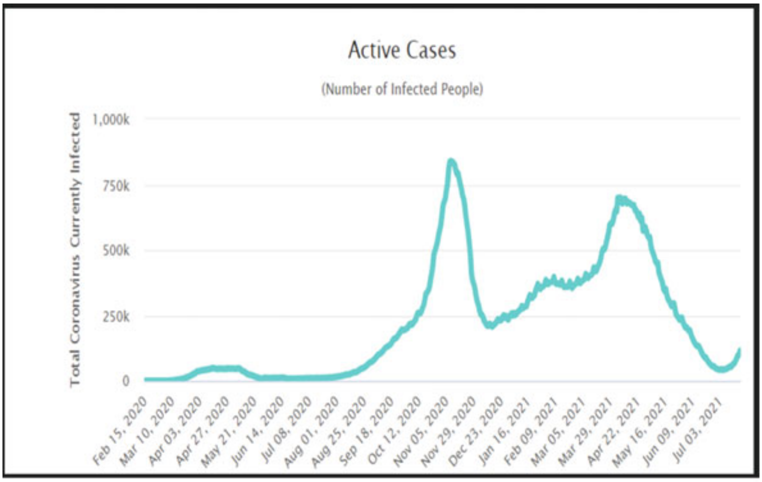
India		Beta	Slope	Alpha	R_0	s_0
1st part of the year	SIR	0.09029	0.03970	0.05060	1.78460	0.56035
	PG-SIR	0.04744	0.02261	0.02483	1.91045	0.40869
2nd part of the year	SIR	0.08729	−0.00308	0.09037	0.96591	1.03529
	PG-SIR	0.07067	0.000826	0.06984	1.01183	0.98831
3rd part of the year	SIR	0.08834	−0.00697	0.95531	0.92691	1.07886
	PG-SIR	0.12292	−0.02424	0.14716	0.83527	1.19607

on it, we have obtained the best fit of the polynomial. For total positive cases, the quadratic fit is the best one while for relatively deceased it is 4th degree fit and for relatively recovered cases, it is cubic polynomial fit.

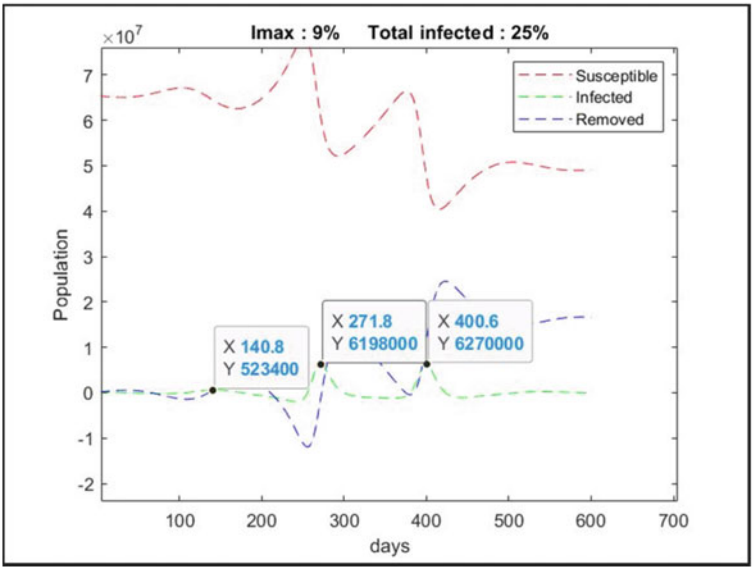
Then after July 2020, three peaks are detected from the PG-SIR model as shown in Fig. 17 a. And the third peak of the model is the predicted one. From the data fed into PG-SIR model, the next peaks are predicted, as can be seen from the graph the PG-SIR model is able to detect the two peaks correctly and the fourth peak of France is expected to come in July end/August starting 2021. At July end/August starting 2021, next peak is predicted as shown in Table 14. The comparison of the SIR and PG-SIR model is shown in Table 15.

5 Conclusions

This chapter has studied the pandemic behaviour for the one year. There exist several models which are being used to analyse the behaviour of the pandemic COVID-19. The chapter has discussed in detail Susceptible-Infected-Recovered (SIR) model along various modifications suggested on the model. This chapter has presented another modified version of SIR model, named PG-SIR (Polynomial Generated Susceptible-Infected-Recovered) model, to study the behaviour of the pandemic. Accordingly, we have considered six mostly affected countries due to COVID-19 to see the effectiveness of PG-SIR model on these countries. It is seen that even though PG-SIR model is a simple model but it has the capability to predict results with accuracy like any complex mathematical model available for the prediction.



(a) Active Cases in France (Worldometer)



(b) PG-SIR Model of France

Fig. 17 Comparison of true peaks of France

Table 14 Calculation of the predicted values of the next peak for France

Peak	Calculation from graph	Month
1	July (100 days) + 140 days	November,2020
2	July (100 days) + 272 days	April,2021
3	July (100 days) + 401 days	July end/August starting, 2021

Table 15 Comparison of SIR and PG-SIR model for France

France		Beta	Slope	Alpha	Basic reproduction number	s_0
1st part of the year	SIR	0.040008	−0.016730	0.056738	0.705130	1.418178
	PG-SIR	0.190744	0.011969	0.178775	1.066952	0.887327
2nd part of the year	SIR	0.072561	0.030447	0.042114	1.722965	0.580395
	PG-SIR	0.051655	0.007438	0.044217	1.168220	0.856004
3rd part of the year	SIR	0.045608	0.006467	0.039141	1.65222	0.858206
	PG-SIR	0.055214	0.003527	0.051687	1.068245	0.936115

References

1. Zhu, N., Zhang, D., Wang, W., Li, X., Yang, B., Song, J., Zhao, X., Huang, B., Shi, W., Lu, R., Niu, P., Zhan, F., Ma, X., Wang, D., Xu, W., Wu, G., Gao, G.F., Tan, W.: China novel coronavirus investigating and research team. A novel coronavirus from patients with pneumonia in China, 2019. N. Engl. J. Med. **382**(8), 727–733 (2019)
2. Umakanthan, S., Sahu, P., Ranade, A.V., Bukelo, M.M., Rao, J.S., Abrahao-Machado, L.F., Dahal, S., Kumar, H., Kv, D.: Origin, transmission, diagnosis and management of coronavirus disease 2019 (COVID-19). Postgrad. Med. J. **96**(1142), 753–758 (2020)
3. Rhodes, T., Lancaster, K., Lees, S., Parker, M.: Modelling the pandemic: attuning models to their contexts. BMJ Glob. Health. **5**(6) (2020)
4. Jewell, N.P., Lewnard, J.A., Jewell, B.L.: Predictive mathematical models of the COVID-19 pandemic: underlying principles and value of projections. JAMA **323**(19), 1893–1894 (2020)
5. Telles, C.T., Roy, A., Ajmal, M.R., Mustafa, S.K., Ahmad, M.A., de la Serna, J.D., Frigo, E.P., Rosales, M.H.: The impact of COVID-19 management policies tailored to airborne SARS-CoV-2 transmission. Policy Anal. **7**(4) (2021)
6. Khalid, M.S., Ahmad, M.A., et al.: COVID-19 and immune function—"a significant" zinc. Orient. J. Chem. **36**(6), 1026–1036 (2020)
7. Mustafa, S.K., Ayaz Ahmad, M., Baranova, V., Deineko, Z., Lyashenko, V., Oyouni, A.A.A.: Using wavelet analysis to assess the impact of COVID-19 on changes in the price of basic energy resources. Int. J. Emerg. Trends Eng. Res. (IJETER) **8**(7), 2907–2912 (2020)
8. Rodrigues, R.F., da Silva, A.R., da Fonseca Vieira, V., Xavier, C.R.: Optimization of the choice of individuals to be immunized through the genetic algorithm in the sir model. In: International Conference on Computational Science and Its Applications, pp. 62–75 (2018)
9. Singh, R., Adhikari, R.: Age-structured impact of social distancing on the COVID-19 epidemic in India (2020). arXiv:200312055
10. Chaves, L.F., Hurtado, L.A., Rojas, M.R., Friberg, M.D., Rodríguez, R.M., Avila-Aguero, M.L.: COVID-19 basic reproduction number and assessment of initial suppression policies in Costa Rica. Math. Model. Nat. Phenom. **15**, 32 (2020)
11. Dhanwant, J.N., Ramanathan, V.: Forecasting COVID-19 growth in India using susceptible-infected-recovered (SIR) model (2020). arXiv:200400696
12. Das, S.: Prediction of covid-19 disease progression in India: under the effect of national lockdown (2020). arXiv:200403147
13. de Oliveira, A.C.S., Morita, L.H.M., da Silva, E.B., Granzotto, D.C.T., Zardo, L.A.R., Fontes, C.J.F.: Bayesian modeling of COVID-19 cases with a correction to account for under-reported cases (2020). medRxiv
14. Postnikov, E.B.: Estimation of COVID-19 dynamics "on a back-of-envelope": does the simplest SIR model provide quantitative parameters and predictions? Chaos Solitons Fractals 135 (2020)

15. Deo, V., Chetiya, A.R., Deka, B., Grover, G.: Forecasting transmission dynamics of COVID-19 epidemic in India under various containment measures-a time-dependent state-space SIR approach (2020). medRxiv
16. Hazem, Y., Natarajan, S., Berikaa, E.: Hasty reduction of COVID-19 lockdown measures leads to the second wave of infection (2020). medRxiv
17. Jakhar, M., Ahluwalia, P., Kumar, A.: COVID-19 epidemic forecast in different states of India using SIR model (2020). medRxiv
18. Mujallad, A., Khoj, H.: Is there hope for the Hajj? Using the SIR model to forecast COVID-19 progression in the city of Makkah (2020). medRxiv
19. López, L., Rodo, X.: A modified SEIR model to predict the COVID-19 outbreak in Spain and Italy: simulating control scenarios and multi-scale epidemics (2020). Available at SSRN 3576802
20. Yang, Z., Zeng, Z., Wang, K., Wong, S.-S., Liang, W., Zanin, M.: Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions. J. Thorac. Dis. **12**(3), 165 (2020)
21. Engbert, R., Rabe, M.M., Kliegl, R., Reich, S.: Sequential data assimilation of the stochastic SEIR epidemic model for regional COVID-19 dynamics (2020). medRxiv
22. Godio, A., Pace, F., Vergnano, A.A.: SEIR modeling of the Italian epidemic of SARS-CoV-2 using computational swarm intelligence. Int. J. Environ. Res. Public Health. **17**(10) (2020)
23. Pandey, G., Chaudhary, P., Gupta, R., Pal, S.: SEIR and regression model based COVID-19 outbreak predictions in India (2020). 200400958
24. Bonnasse-Gahot, L., Dénès, M., Dulac-Arnold, G., Girgin, S., Husson, F., Iovene, V., et al.: ICU bed availability monitoring and analysis in the Grand Est region of France during the COVID-19 epidemic (2020). medRxiv
25. Dixit, A., Vishnoi, S., Paul, S.B.: Adding structure to statistics: a study on COVID-19 dynamics in India (2020). medRxiv
26. Kohanovski, I., Obolski, U., Ram, Y.: Inferring the effective start dates of non-pharmaceutical interventions during COVID-19 outbreaks (2020). medRxiv
27. Teles, P.: A time-dependent SEIR model to analyse the evolution of the SARS-CoV-2 epidemic outbreak in Portugal (2020). arXiv:200404735
28. Wagh, C.S., Mahalle, P.N., Wagh, S.J.: Epidemic peak for COVID-19 in India (2020)
29. Ray, D., Salvatore, M., Bhattacharyya, R., Wang, L., Mohammed, S., Purkayastha, S., et al. Predictions, role of interventions and effects of a historic national lockdown in India's response to the COVID-19 pandemic: data science call to arms (2020). medRxiv
30. da Cruz P.A., Cruz L.C.C.: Mathematical modeling and epidemic prediction of COVID-19 of the State of São Paulo, Brazil. Int. J. Adv. Eng. Res. Sci. **7**(5) (2020)
31. Kobayashi, G., Sugasawa, S., Tamae, H., Ozu, T.: Predicting intervention effect for COVID-19 in Japan: state space modeling approach. Biosci. Trends **14**(3), 174–181 (2020)
32. de León, U.A.-P., Perez, A.G., Avila-Vales, E.: An SEIARD epidemic model for COVID-19 in Mexico: mathematical analysis and state-level forecast (2020). medRxiv
33. Rajesh, A., Pai, H., Roy, V., Samanta, S., Ghosh, S.: CoVID-19 prediction for India from the existing data and SIR (D) model study (2020). medRxiv
34. Khatua, D., De, A., Kar, S., Samanta, E., Mandal, S.M.: A dynamic optimal control model for SARS-CoV-2 in India (2020). Available at SSRN 3597498
35. Kermack, W.O., McKendrick, A.G.: Proceedings of the royal society of London series A, containing papers of a mathematical and physical character, vol. 115. A contribution to the mathematical theory of epidemics, pp. 700–721 (1927)
36. Bagal, D.K., Rath, A., Barua, A., Patnaik, D.: Estimating the parameters of susceptible-infected-recovered model of COVID-19 cases in India during lockdown periods. Chaos Solitons Fractals. **140**, 110154 (2020)
37. Coronavirus Outbreak in India. http://www.covid19india.org
38. https://www.statisticshowto.com/rmse-root-mean-square-error
39. https://www.corporatefinanceinstitute.com/r

40. Ugoni, A., Walker, B.: The Chi square test: an introduction. COMSIG review/COMSIG, Chiropractors and Osteopaths Musculo-Skeletal Interest Group **4**, 61–64 (1995)
41. COVID-19 pandemic in the United States—Wikipedia
42. COVID-19 pandemic in India—Wikipedia
43. COVID-19 pandemic in the United Kingdom—Wikipedia
44. COVID-19 pandemic in Russia—Wikipedia
45. COVID-19 pandemic in France—Wikipedia
46. COVID-19 pandemic in Brazil—Wikipedia
47. Total COVID-19 tests (http://www.ourworldindata.org)

Digital Contact Tracing for COVID 19: A Missed Opportunity or an Expensive Mess

Syed Imran Ahmed and Sheikh Mohammed Shariful Islam

Abstract Digital contact tracing is one of the critical components for managing the COVID-19 pandemic adopted by many countries. Individuals with a certain level of exposure are identified using digital technologies like low-energy Bluetooth signals, GPS, and wifi combined in a smartphone application. Despite its rapid adaptation by many countries and heavy investment in developing this technology for rapid control of disease transmission, results have been mixed. Scientists have identified several causes like disparity in smartphone usage, a diverse adaptation of contact tracing protocols, the geographical disparity in the use of technology, and lack of adaption with low adherence responsible for this inevitable failure. Though digital contact tracing missed achieving its anticipated goals, it has provided extensive information to design a better technique in future outbreaks. Key approaches to resolving these problems include eliminating privacy concerns, improving protocol to achieve better signal with higher accuracy, feeding background data in the application for machine learning and adopting advanced technology like blockchain. Overall, the geographical disparity in technology adoption should be considered before investing in any digital intervention.

Keywords Contact tracing · Digital contact tracing · Mobile apps · COVID-19 · Digital technology · Disparity · Quarantine · Tracking · Low-energy bluetooth technology

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1 Introduction

Infectious diseases are also known as transmissible or communicable diseases resulting from an infection. Many infectious agents, predominantly viruses, bacteria, and protozoa, are responsible for spreading infection [1]. In a few cases, the infection spreads rapidly and reaches an epidemic stage even before developing the prophylactic measures. Therefore, controlling such diseases as Severe Acute Respiratory Syndrome (SARS), influenza, and COVID-19 are way too tricky than a disease with lower infective capabilities [2]. Concentrating control measures among the observed cases using all resources may not be adequate to control the disease with higher spreading capabilities. Often health authorities suffer in a dilemma that some infectious agents of carriers are yet to be observed, which creates a critical situation to control contagious diseases like SARS, MARS, and COVID-19. On contrarily, directing entire resources to prevent the disease for the population (mass vaccination, prophylactic treatment, preventive culling) will contain the disease at a higher cost and a longer duration [3]. Therefore, despite aiming towards a pharmacological solution to control these highly contagious diseases, pre-emptive culling can successfully prevent the infection at the earliest [4]. Among many approaches, control measures with specific target groups have dramatically increased in efficiency [5, 6].

Contact tracing is a critical component in preventing infectious diseases by identifying people who encountered an infected individual for a certain period [7]. Traditionally, dedicated individuals called contact tracers are appointed to perform the tracing, and the length of the contact tracing by these individuals depends on disease type and severity. In contact tracing, follow-up with cases and subsequent isolation has shown a better reduction in community transmission. It is a recommended policy for tackling outbreaks of new or reemerging infections and has been used in the past to eradicate diseases [8]. Conventionally, contact tracing starts with the identification of new cases of an infectious disease. Patients are then interviewed to identify their contacts in the recent past (from the recall of the last 2–3 days before symptoms onset). Afterwards, those identified contacts are notified about their exposure status and requested to self-isolate or seek institutional isolation, followed by a possible self-test. This enormous procedure is undertaken to interrupt viral transmission chains [9]. However, such manual contact tracing has some fundamental issues like time delays, is resource-intensive and limited by the recall bias of the infected individuals. In addition, by nature, people tend to avoid confrontation and are afraid of isolation [10, 11]. Therefore, interview-based contact tracing can fall short of the required capacity when the infection becomes widespread.

The current scenario of COVID-19 has surpassed everything we have ever experienced and outsmarted the capacity of every government to contain this pandemic through manual contact tracing [12]. As of mid-May 2021, nearly 160 million people were infected by COVID-19, and over 3 million deaths were caused by this deadly virus, with a case fatality rate of 3% in 219 countries [13]. Given the high transmission capacity of COVID-19 and the high number of asymptomatic cases (59%

reported by CDC), manual contact tracing is unlikely to be sufficient to control this pandemic [14].

2 COVID 19 and Digital Contact Tracing

Coronavirus disease 2019 is a highly infectious, aggressively spreading disease caused by severe acute respiratory syndrome coronavirus 2 or SARS-CoV-2, a member of beta coronavirus and successor of SARS-CoV-1 or SARS virus [15]. After the first appearance of this virus in Wuhan, China, in late 2019, it rapidly spread throughout the world in such a way that the World Health Organization (WHO) had to announce it a global pandemic on 11 March 2020, just after three months of the first appearance [16]. This deadly virus has caused many deaths, disabilities, affected lifestyle behaviours [17–19], Muhammad Aziz [20, 21], psychologiocal health and impacted health systems throughout the world [20, 22, 23, p. 19, 24, 25]. Besides its lower-case fatality rate, almost 5% of the total cases require intensive care support, which is exceptionally challenging for the health systems when cluttered by non-communicable diseases [26, p. 19]. Unlike other infectious diseases, the management of COVID-19 is far complicated for requiring personal protective equipment and ensuring a complex decontamination method which is expensive and has a worldwide shortage [27]. Fatality rates are likely higher among the older population and low resource settings where critical care management is lacking [28]. Since it emerged, COVID-19 has brought the world to its knees. The rapid escalation of contamination forced countries to impose drastic measures like imposing travel bans, closure of educational institutions, industries, offices, shopping malls to achieve social distancing [29]. In the absence of proven pharmacological interventions to provide absolute prevention or treatment, contact tracing remains a critical component to contain this global pandemic. As countries struggle to cope with the current health care systems, the WHO and several governments have explored an alternative pathway to addressing this crisis using a technology-based solution.

Contact tracing, explicitly identifying people who encountered an infected individual, is one of the proven components among all control measures generally adopted for the infectious disease. The existing method of contact tracing is resource-intensive, sluggish in nature, subject to recall bias, and impractical for a disease like COVID-19. For example, identifying possible contacts of an infected individual in New Zealand takes dedication for three to five-person for several days, and only 80 cases per day vanquished/crushed the entire system. In contrast, the United States (US) exhibited more than 0.3 million daily cases in early January 2021. Therefore, a better way to identify cases and impose isolation was mandatory. In response to the crisis, several countries and technology giants came forward to accelerate contact tracing through digital methods using mobile devices, electronic data servers and machine learning technology. However, this technology-driven solution might provide solutions to relax the lockdown and keep the transmission in check by identifying possible exposure followed by testing and isolation. However, its effectiveness is yet to be understood where transmission and infection continue at a higher rate.

Though none of the countries has revealed their actual cost of developing and maintaining these apps yet, the report suggests they cost a fortune for each country. Numerous reports surfaced from different continents indicating the approximate expenditure behind these apps; for instance, the NHS reportedly cost 35 million USD behind their NHS Covid-19 app [30]. The German government expended approximately 22.5 million USD [31], which is undoubtedly higher than any means. After initial rapid adoption, most of the apps had been abandoned or not been used. We can understand from the example from India, where apps received the highest downloads, but resurgence occurred due to relaxation and less vigilance in monitoring the COVID-19 situation [32].

3 Issues that Have Obscured the Efficacy of Digital Contact Tracing

Theoretically, contact tracing should work like a samurai sword against such contagious diseases as COVID-19 by cutting down the spread of the disease by preventing human-to-human transmission. The current advanced technologies and extensive use of smartphones have created a vast opportunity to use this app-based contact tracing as a powerful tool to limit disease transmission during the pandemic [33]. However, the current scenario does not translate the aim of this extensive initiative into a reality in all cases [34]. Countries have undertaken numerous approaches to correct the pathway of contact tracing and readjusted the methods. Many technology companies have come forward to support this initiative by creating their tracking system [35]. This intervention resulted in different ways in different places. For example, South Korea and Singapore have successfully created their digital contact tracing system and rapidly cut the transmission [36]. In contrast, India and the United States (US) have failed to use this approach despite having numerous efforts behind this intervention [34, 37]. There are multiple causes suspected of its failure. The possible reasons that hinder its outcomes are discussed below.

3.1 Privacy Concerns

Inherently, contact tracing concerns individual privacy by sharing data with the contact tracer or the central authority. In manual contact tracing, individuals share personal information with the contact tracers, eventually sharing it with the central authority. In contrast, automated apps do not require sharing those data directly to the individual tracer or central authority but possess other privacy concerns [38]. Some of the apps use global positioning systems (GPS) data to track down the movement of the infected individuals. Personalized data collected from the apps are promised to be encrypted and secured by an authorized body [39]. However, evidence suggests that nothing is breach-proof in the modern world, and personalized data can be used for business or as a weapon if it falls to the wrong hand (Du et al., 2018).

Organizations working for digital rights worldwide have been vocal about the need and technique of contact tracing technology to safeguard civil liberties and their privacy [40]. In an ideal world, adopting any such technology with tracking features like contact tracing must be conducted under voluntary participation and should be adopted based on informed consent after having necessary trust in the efficacy of the technology and governing institutions [41]. To achieve this trust in the general population, we must ensure transparency, legality, and well-enforced data protection.

In reality, we have observed that governments have rushed to implement tracing apps using a centralized data collection system where servers are maintained by the government [42]. Many initial attempts have suffered from mission creep; technologies were designed and operated by private organizations with a lack of public oversight, no legal framework and sketchy privacy protection measures, and accountability [40]. Therefore, the overall situation is threatened by a lack of public trust and low adaptation of the tracing apps. A survey conducted in April 2020 in the US showed that people have a very low level of trust in tech companies, educational institutions, insurance companies, and government health organizations [43]. Consequently, many apps were created in the US by both government and private authorities and shallow adoption of these apps combinedly than other developed countries [44]. However, the scenario for privacy concerns does not apply as it should be for low- and middle-income countries. Low education levels among the general population and sub-optimal human rights practices provoke this privacy issue [45].

3.2 Technological Disparity

The implementation of this technology-based solution largely depends on the level of penetration of smartphones. While developed countries have excellent penetration required for contact tracing, only 42–45% of worldwide own a smartphone [46]. Only about three-quarters of the devices support the necessary low-energy Bluetooth technology, which is essential for digital contact tracing [47]. This translates to even lower availability for those vast numbers of people living in developing countries, where smartphone penetration is insufficient. There is a staggering difference between smartphone owners in different countries. It correlates with the Gross Domestic Product (GDP) per capita and the percentage of smartphone users in a country shown in Fig. 1. In low-income countries, one in every 10 people use a smartphone, wherein in the wealthier countries, this ratio rises to nine in every ten people. This number is eight to nine times higher in the high-income countries meaning only one or two out of 10 people do not have one [48]. For example, in Tanzania, only

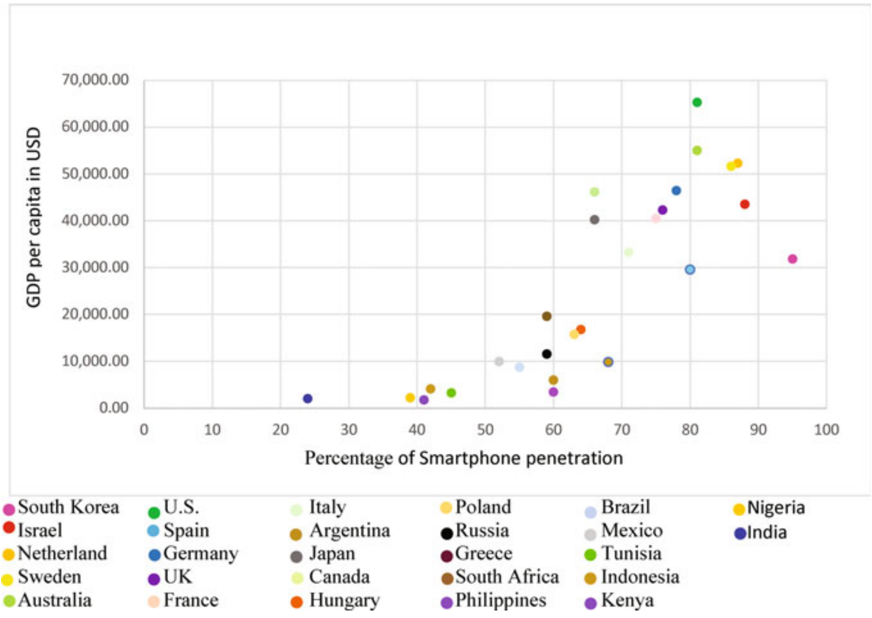

Fig. 1 Comparative analysis of smartphone penetration and per capita GDP [51]

13% of people use smartphones [49], whereas 97.13% of people in South Korea own at least one smartphone [50].

On the contrary, low penetration of mobile internet is also a significant impediment to this intervention. Global System for Mobile communications Association (GSMA), a representative of the worldwide mobile operators, uniting over 750 operators, has shown in the latest report, 26% of the population is connected via mobile internet subscription, whereas 76% of people living in Europe have subscribed to mobile internet. Internet connectivity is necessary for the contact tracing apps to work (to upload data personalized data to the server), is similarly unevenly distributed, abandoning half of the entire population, 3.5 billion without access to the internet [52].

The disparity in access to the usage of smartphones and mobile internet remains a global problem. It seems the authority often overlooks this digitally divine scenario within the countries. For instance, the elderly population is more vulnerable to COVID-19 because the specific group with the lowest smartphone and internet usage compares to the younger counterparts. According to the independent survey, smartphone penetration in Europe is above 75%, higher than the global average. However, the disparity is observed among different age groups where young adults (18–35 years) own smartphones are 1.5 times than those aged more than 50 years [12]. This difference is incredibly high in countries with low general smartphone ownership. In India and Indonesia, where penetration levels are generally low, young people are as much as five times more likely to own a smartphone than those over 50 years, shown in Table 1.

A significant difference is observed between the different demographics in the US, where overall usage is higher than the global standard. According to a recent survey, only 53 out of 100 people aged 65 years or older use smartphones, whereas this number is staggeringly high at 96% among the people aged between 18–29 years. Therefore, 24 million people are left behind when a nationwide campaign is conducted for smartphone-based digital contact tracing [51]. Survey also reported

Table 1 Disparity in smartphone use among different age groups [51]

Countries	Total	Age			Youngest-oldest gap
		18–34	35–49	50+	
South Korea	95	99	100	91	8
Israel	88	91	94	80	11
Netherlands	87	99	98	74	25
Sweden	86	98	92	77	21
Australia	81	97	89	68	29
The U.S	81	95	92	67	28
Spain	80	95	93	60	35
Germany	78	98	90	64	34
The UK	76	93	90	60	33
France	75	97	91	53	44
Italy	71	98	91	48	50
Argentina	68	84	77	42	42
Canada	66	90	85	43	47
Japan	66	96	93	44	52
Hungary	64	92	84	35	57
Poland	63	93	87	35	58
Greece	59	95	83	29	66
Russia	59	91	76	26	65
Brazil	60	85	63	32	53
South Africa	60	73	59	35	38
Philippines	55	74	50	27	47
Mexico	52	66	53	30	36
Tunisia	45	75	35	18	57
Indonesia	42	66	32	13	53
Kenya	41	51	27	18	33
Nigeria	39	48	31	20	28
India	24	37	21	8	29

that household income or wealth capacity is a decisive factor for owning a smartphone because of the popularity of user-friendly basic phones among the older population.

The scarcity of data from the low-and-middle-income countries often makes it difficult to understand the ultimate scenario of the intervention as we can for the US or Europe. For instance, only 18.5% of people in Bangladesh are using smartphones [53]. There are 94 million mobile internet subscribers in Bangladesh, with a higher number of sim card users, indicating that most use the internet on non-smartphones or feature phones [54]. The non-smartphones cannot install 3rd party apps and lack low-energy Bluetooth technology.

Data also illustrates the gender inequality in access to technology. In Iraq, regardless of the wealth disparity or geographical divergence between urban and rural areas, most households own at least one mobile phone. However, less than half of the women in the poorest household have access to that mobile phone when it comes to actual usage. A Pew research conducted in 2018 showed that less than half of the women in India have access to a smartphone than men (15% compared to 34%) [51]. In Bangladesh, due to the lack of education and low affordability, only 30% of males and 13% of females use mobile internet regularly among mobile users [55].

The geographical disparity in technological distribution is another bottleneck for this kind of advanced intervention. There is lower penetration of smartphones in the rural areas in the US compared to their urban counterparts (71% vs. 83%) [51]. This disparity climbs to an alarming rate in low and middle-income countries due to lower education and income facilities in rural areas. This problem shines further when a majority of the population resides in rural areas. For instance, 62.5% of people living in rural Bangladesh have insufficient infrastructure and tremendous educational and socioeconomic disparity compared to urban society [56]. Additionally, major cities also suffer from the rapid growth of densely populated slums with a lack of social distancing and no meaning of isolation. Nearly one billion people live in such a condition with a short supply of sanitation service, waste management, clear water, and necessities. As a result, a significant number of the population can be left behind to implement this intervention. These places have emerged as a hot spot for COVID-19 transmission [57]. In addition, they are also connected with the other parts of the cities through work and other daily services. Keeping them out of this intervention makes can it more plan vulnerable than ever.

Epidemiologists suggested that to succeed in smartphone app-based digital contact tracing, at least 60% of the population must be covered for identifying and isolating infections within a few days [58]. This ratio will vary depending on the percentage of affected people and what isolation and distancing measures are placed for further assistance. Effective contact tracing cannot be achieved if 60% of countries population does not own a smartphone regardless of gender and geography. Rolling out contact tracing apps without taking gender, age, wealth, ability, race, and class aspects of the digital divide into account can be disastrous and exacerbate problems for the most vulnerable.

3.3 Epidemiological Scrutiny

Despite major impediments, many developed countries have already deployed their digital contact tracing apps using different protocols. The low-energy Bluetooth technology protocol using the Receiver Signal Strength Indicator (RSSI) is the most popular with better safeguards against individual privacy [59]. Following the footsteps of the developed countries, low and middle-income countries also launched their apps (Table 2). Though we agree this is the best possible technology to date, it does not assure its adequacy to correctly identify the exposure to gain proper epidemiological impact [60].

To contact tracing app needs to be downloaded from a specific app store (Apple or Google app store mostly) or designated website before use. While using the app, it must be enabled on the phone to broadcast a short burst of data using a Bluetooth signal every few seconds. Other phones having similar apps around that phone will detect this signal using RSSI and measure its strength. To reduce power wastage, it broadcasts low energy signals. The smartphone receives these signals, and in theory, a strong signal means that the devices are near each other; the further they are, the weaker the signal [59].

In an ideal scenario with enough smartphones at play, transmitted Bluetooth signals are the most powerful that other smartphones can pick up to 100 m (330 ft). This is way above the recommended 2 m (6 ft) distance to avoid person to person infection. Current apps depend on two major mechanisms:

(1) lowering the power of transmission to avoid misidentification of exposure through such long-distance signals
(2) relying on Bluetooth signal strength measurement to identify short-distance proximity events—they assume a strong signal means a short distance. In contrast, a weak signal means two people were further away from each other.

However, during contact tracing, these two methods do not work as expected. For instance, the human body can absorb these transmission signals or be obstructed by nearby objects, weakening the signal strength. This means which signal strength can vary significantly between two people depending on the presence of the smartphone at their front or back pocket or their hand. Simultaneously, Bluetooth signals can pass thin walls of a household and be picked by people using the same app, staying on another side of the wall and identified at exposure. Additionally, studies have shown this Bluetooth technology was unable to differentiate 1-m versus 3-m distance using the same protocol currently using those contact tracing apps. This brings the question of eligibility for this method to achieve an epidemiologically important measurement [48, 62].

This problem mentioned above will amplify when used in different phone models with other networking capacities and people carrying different places regarding their body while travelling [48]. However, this problem can be toned down if there is tight integration with the Apple and Google API, where signal strength will be kept different depending on the capability of the respective smartphone. The code that

Table 2 Contact tracing app downloads from Google Play Store by countries [61]

Name of the Country	Name of the app	Downloads	Population
Australia	COVIDSafe	1,000,000+	25,365,740
Austria	Stopp Corona	100,000+	8,879,920
Belgium	Coronalert	1,000,000+	11,502,700
Brazil	Coronavirus-SUS	5,000,000+	211,049,530
	Tô de Olho	10,000+	
Canada	COVID Alert	1,000,000+	37,593,380
	AbTrace Together	100,000+	
Czech Republic	eRouška	1,000,000+	10,671,870
Denmark	Smittelstop	500,000+	5,814,420
Ecuador	ASI	500,000+	17,373,660
Fiji	CareFIJI	100,000+	889,950
Finaland	Koronavikku	1,000,000+	5,521,610
France	TousAntiCovid	5,000,000+	67,055,850
Georgia	Stop Covid	1,000,000+	3,720,160
Germany	Corona-Warn-App	10,000,000+	83,092,960
Gibraltar	BEAT Covid	10,000+	33,760
Greece	DOCANDU Covid Checker	1000+	10,717,170
Hong Kong	LeaveHomeSafe	1,000,000+	7,507,400
Iceland	Ranking C-19	100,000+	360,560
Ireland	COVID Tracker Ireland	500,000+	4,934,040
Israel	Hamagen	1,000,000+	9,054,000
Italy	Immuni	5,000,000+	60,302,090
Japan	COCOA - COVID-19 Contact App	5,000,000+	126,264,930
Malaysia	Gerak Malaysia	1,000,000+	31,949,780
Netherlands	CoronaMelder	1,000,000+	17,344,870
New Zealand	NZ COVID Tracer	1,000,000+	4,979,300
Norway	Smittestopp	100,000+	5,347,900
Poland	ProteGO Safe	1,000,000+	37,965,470
Portugal	STAYAWAY COVID	1,000,000+	10,286,260
Singapore	TraceTogether	1,000,000+	5,703,570
South Korea	Corona 100 m	1,000,000+	
South Africa	COVID Alert South Africa	1,000,000+	58,558,270
Spain	Radar COVID	5,000,000+	47,133,520
Switzerland	SwissCOVID	1,000,000+	8,575,280
United Kingdom	NHS COVID-19	10,000,000+	66,836,330
United States	Covid Watch	10,000+	328,239,520

(continued)

Table 2 (continued)

Name of the Country	Name of the app	Downloads	Population
	NOVID	10,000+	
	Private Kit: Safe Paths	10,000+	
	COVID Defense	50,000+	
	COVIDDaware MN	100,000+	
	AlohaSafe Alert	50,000+	
	Jersey COVID Alert	10,000+	
	SlowCOVIDNC	100,000+	
India	Aarogya Setu	100,000,000+	1,366,417,750
Bangladesh	Corona Tracer BD	500,000+	163,046,160
Pakistan	Covid-19 Gov PK	500,000+	216,565,320
Nepal	Hamro Swasthya	100,000+	28,608,710
Srilanka	Slef Shield	5,000+	21,803,000
Indonesia	PeduliLindungi	5,000,000+	270,625,570
Vietnam	Bluezone	10,000,000+	96,462,110
Ghana	GH COVID-19 Tracker App	10,000+	30,417,860

translates signal strength to distance will need to be further calibrated for different scenarios. This translation will be different outside vs inside, for phones carried in front pockets vs back pockets, backpacks vs purses, and so on [48]. This demands a more challenging job for the entire app developed team, where Android, the most used platform for smartphones, has thousands of models with varying capacities. However, there is no unified app for all people; somewhat different countries are making their version, even these apps varies by region within the country [63]. Therefore, depending on a specific app is difficult when there is limited information documented on their accuracy.

In addition, to work perfectly, these apps require Bluetooth to be kept on for the entire time, a major battery drainer [64] Both Apple and Android have auto power-saving features, which will be activated during the lower power mood and can switch those signals. Individuals can also switch them off manually to extend the remaining battery life. That can create an additional obstacle for the apps to work correctly [65].

Lastly, viral transmission pathways cannot be captured through these apps. For instance, viral transmission in airconditioned restaurants or hotels works on a whole different level. Even though the infected person sitting at a proper distance or staying in different rooms does not ensure complete safety despite being undetected by the app. This contamination can transfer through the air duct or used utensils [66].

Every technology used to diagnose or identification are subject to two kinds of errors: False-negative and False positives. Bluetooth-based contact tracing faced similar issues like failure to report a potential exposure or contact via miscalculation in the distance, low or empty charged battery, or lack of smartphone or apps to the infected person. False-positive is reported when a person is on another side of the wall, tightly sealed room or staying above the roof. Both scenarios can drive the person to take the opposite action, like being confined in quarantine or avoiding it accordingly. False-positive will happen commonly in a densely populated area, in public transport or the shared working space. Both scenarios will provoke trust issues among the population regarding the app [48].

Despite having numerous flaws, it is still the best digital option we have currently to fight against this pandemic. Bluetooth is more accurate than GPS-based solutions and works faster than GPS with insufficient data and energy requirements. Most of the data generated by the researcher to back this intervention are taken from simulation tests to calculate the spreading dynamics.

3.4 Adoption of Tracing Apps

Experience from different countries deployed this app-based intervention significantly varies. Data regarding the adoption rate is sketchy. None of the governments released their active number of users for their respective apps. Between the two popular platforms, Apple does not release the download status of any apps, and Google provides only a rough estimation [48]. Still using the download numbers, a rough estimate is shared in Table 2. These numbers do not reflect the apps actual usability or adaptation, and they can only share the possible number of people who got in touch with the app.

The first country that has successfully launched the application was Singapore called "Trace Together" which failed to keep up with the promises of data minimization and privacy safeguards and the opening of the app source code. Only 1.1 million (or less than one in five) residents installed it six weeks after deployment. That is far below the minimum goal of 75%, set by their national response team [67]. The Australian App COVIDSafe reached the initial 2 million download very fast, then stalled [68]. Two weeks after the deployment, contact tracing apps had 860,000 downloads in Norway, covering only 16% of the population [69]. In Figure 2, we can see the overall adoption of the contact tracing apps in different countries, reflect how this intervention lacked the necessary intake among people to curve down the pandemic.

In terms of developing countries, this scenario turns into a nightmare. Corona Tracer BD, an app developed by the Bangladeshi government, was launched in late May 2020 with a skyrocketing expense. To date, it has just over 0.5 million downloads which are negligible for a country having a population above 163 million. It is the same for the rest of the developing world except India. "Arogya Setu" an app developed by the Indian government, was mandated by law for download and became the fastest downloaded apps among all tracers and reached 182,800,000 downloads [71, 72]. However, the current resurgence of COVID-19 in India does not support this enormous downloading status. It indicates that Indians did not adhere to the app after downloading and observed the worst COVID-19 outbreak in history [73].

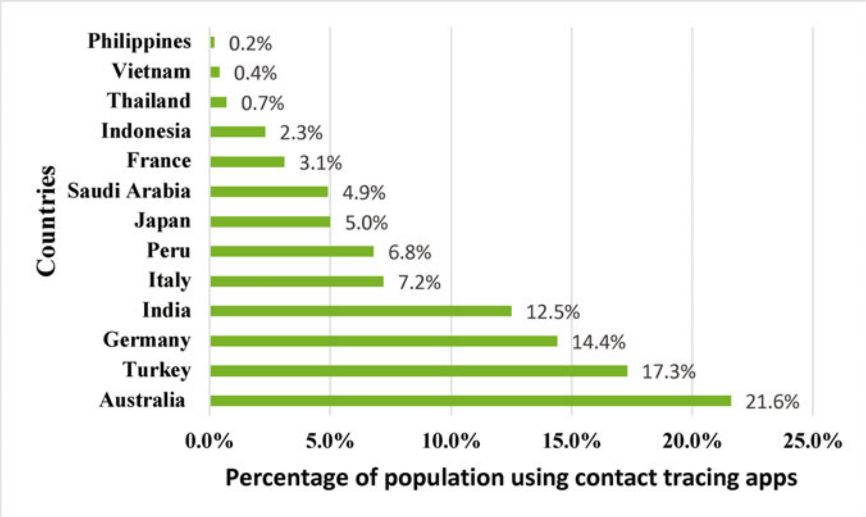

Fig. 2 Adoption of government-endorsed contact tracing apps in different countries [70]

4 Contact Tracing Could Not Be Done Alone

Contact tracing effort is most effective at the start of the epidemic curve when such measures are more manageable in terms of cases. In the hypothetical scenario, every case will be identified quickly through further testing and identified contacts are notified for self-quarantine or institutional approach. These targeted tactics could stifle local epidemics. However, relaxing strict isolation measures before developing the required infrastructure, which are prerequisites to ensure proper social distancing through contact tracing, is not recommended, specifically in those countries where health care is still decentralized and fragmented [74]. Contact tracing is also not recommended for those communities with the sustained ongoing transmission with a high infection rate [7].

Comprehensive contact tracing measure requires proper forethought, coordination, communication and social acceptance of the outcomes. Many countries failed to keep up with their efforts for contact tracing, where there was a lack of testing facilities and proper quarantine measures [75]. Countries with a low level of education prevent them from understanding the need to contact tracing and high density of population drives for the sure failure of quarantine measures. The lack of synchronized public health systems with legal authority also drives this intervention as a failure. Very few countries like South Korea have drawn a successful example for these contact tracing measures. South Korea experienced severe acute respiratory syndrome (SARS) and the Middle East respiratory syndrome (MERS), which helped them modify their legislation after those outbreaks to prepare themselves for prompt response against this kind of epidemic. Therefore, South Korea could integrate patient interviews, medical records, GPS from mobile phones and track their movement, facial recognition using closed-circuit television (CCTV) footage, and credit card transaction data to enrich the tracing mechanism [75]. They also motivated people for the COVID-19 case tracing beforehand when the world is just observing new cases surging everywhere. In the case of Taiwan, their health system managed to integrate data from the health insurance records, previous medical data from online servers, travel history, and data from both an app and a toll-free hotline set up for the public to report suspected cases [76, 77, p. 19]. Such methods will not be applicable for all countries where privacy is a big concern or lack of technology and data synchronization.

5 Recommendations

At present, health systems globally are overwhelmed by the extra burden enforced by this pandemic. Countries like India, Brazil, and the United States struggle to provide necessary care for the patients even if oxygen requirements cannot be maintained [78, 79]. The proper contact tracing effort could have curtailed down the transmission cycle and allowed managing this at the earliest. However, uncoordinated sporadic app development with minimum to no confidence among the general population resulted in fewer adaptations followed by failure of the intervention [34]. To overcome these backlashes, we recommend a few approaches to be applied which might eventually influence its wide acceptance and adaptation:

There have been several methods developed to secure the price in contact tracing efforts. First, there should be an optimum balance between user privacy and the benefit of society while using user-specific data curated from contact tracing apps. Many experts recommend decentralized Privacy-Preserving Proximity Tracing (DP-3 T) for contact tracing [80]. This backend server system can block the use of location data by the main server. Data identifying the participants and location should be stored locally on devices and not sent to a central server. Records that are to be shared with the authority must be encrypted. Data collected for this method must be used only for public health purposes. The source code of the app should be made publicly available to further analysis by other experts. Participation in such an extensive measure should be voluntary, and every user should give proper consent to understand the possible outcomes. It is suggested to build an independent non-biased technical committee with legal, health, and privacy experts to oversee the entire procedure. Data collected throughout this pandemic must be deleted when the pandemic is over [81].

Second, all security-related issues should be handled with the uppermost priority and must be solved before rolling out the final version and taking prompt action for the already rolled out ones. The experts recommend that BLE signals must be regulated in all standardized manners [82]. Legislation should be put to rollout software related issues specifically for android mobiles with Bluetooth vulnerability due to lack of OS update among the older devices [42].

Third, to extend the epidemiological acceptability, the current technique of contact tracing using the BLE signal should be updated. Proximity accuracy can be solved using machine learning technology, keeping in mind all the different smartphones with variable capacity. BLE is the current best low-cost technology at our hands. There is still room for improvement in the efficiency of using newer refined protocols for BLE signal calibration [59, 83].

Fourth, at present, there are very few surveys and studies to understand the general perspectives on contact tracing. Therefore, there is a gap between the implementer and the user of this intervention. We need to understand the psychological factors that would prevent or motivate them to adopt contact tracing at present [84, 85]. This would give us a pathway to design a social campaign that will encourage people to adopt the intervention with a proper understanding of possible scenarios of contact tracing. Studies suggest that people would respond positively if their security concerns were handled at the highest priority, emphasizing their autonomy and clearly describing the social benefits. Finally, people need to realize their overall societal advantages before rolling out any mass contact tracing measures [86].

Fifth, it has been evident that the inclusion of previous records, medical reports, and advanced technology can boost the effort of contact tracing. However, extensive use of technology can harm a privacy issue that many experts have already identified. Therefore, we need to find a middle ground where we can include additional monitoring technology with minimum to no risk of privacy breach, which will ultimately increase the accuracy of the tracing effort. In addition, studies have proven that wearing a mask can and maintain personal hygiene can reduce the transmission of infection. Having a vaccine is shown to have a much better impact than any of the other measures. However, none of the vaccines can prevent the disease entirely [87]. Therefore, social distancing still needs to be intact, and information regarding vaccination and personal hygiene can be added to the application as a reminder.

Sixth, the introduction of Blockchain-based digital contact tracing can be a pathway to solve the issues for privacy and security of the users. Blockchain-chain apps can play a significant role in contact tracing by maintaining peer-to-peer connectivity and allowing data sharing while preserving privacy [12]. The current practice of a centralized network for data management systems is subjected to data breaches and manipulation [88, 89]. A brief description of the default properties of blockchain-based contact training is mentioned in Table 3.

Finally, contact tracing app could be integrated with other smartphone based health applications for disease screening, covid-19 vaccination passports, which could provide additional benefits [90, 91]. Furthermore, these apps could also integrate with machine learning approaches to screen for possible infection with COVID-19 [92–97].

In blockchain-based system allows deidentifying the users' information right at the beginning. Due to the uniqueness, data accessibility, and traceability, blockchain-based can be used in cross-country intervention and connect globally. This can remove one of the significant drawbacks of app variability.

Finally, contact training is suggested for those communities where the infection is at a lower rate. It is also proven to work if supported by the increased number of testing facilities followed by proper isolation of the infected person [34]. In many places where the testing kit remains rare, only contact tracing will not provide sufficient

Table 3 Application of different features of blockchain-based technology in the digital contact tracing [98]

Feature	Application
Decentralized network	The management of the data is user-centric, which gives the power of data ownership to the users
Data security	The data within the blockchain is kept after applying encryption, which an authorized user can only decrypt
Data provenance	The information is entered in the blockchain is stamped with the digital signature of the source, which proves the legitimacy of the source as well as the data
Data availability	The data are distributed among all the nodes within the network, which makes them available all the time to every user
Data immutability	The information in the blockchain is immutable, which means once the detail is entered, it can never be modified. This provides reliability and transparency to all users
Timestamping	The data within the blockchain network is time-stamped, which eliminates the chances of discrepancies being present

impact to curtail the curve [99]. However, recent evidence suggests that regardless of a different variety, with proper fit, simple measures like wearing a mask can reduce spread deal [100, p. 19, 101].

6 Conclusion

As a consequence of COVID-19, there are unprecedented challenges for public health authorities and require numerous changes to adapt to the scenario. This enormous pressure has brought radical changes to both individual life and organizational procedure. In order to stop the viral transmission and manage the pandemic, governments worldwide have taken many steps and contact tracing app is one of the significant ones. Amid a pandemic, any intervention with such cost that turns into massive failure can hurt the country's economy in a pretty brutal way. Although an enormous failure in Brazil and India, South Korea and Hong Kong showed a clear example of how contact tracing could be a fruitful intervention for the mass population. However, for these app-based contact tracings to succeed, it is important to gain trust among people and address privacy concerns and improve the accuracy of its findings.

References

1. Kotra, L.P.: Infectious diseases. In: XPharm: The Comprehensive Pharmacology Reference. Elsevier, pp. 1–2 (2007). https://doi.org/10.1016/B978-008055232-3.60849-9
2. Petersen, E., Koopmans, M., Go, U., Hamer, D.H., Petrosillo, N., Castelli, F., Storgaard, M., Al Khalili, S., Simonsen, L.: Comparing SARS-CoV-2 with SARS-CoV and influenza pandemics. Lancet. Infect. Dis. **20**, e238–e244 (2020). https://doi.org/10.1016/S1473-3099(20)30484-9
3. Klinkenberg, D., Fraser, C., Heesterbeek, H.: The effectiveness of contact tracing in emerging epidemics. PLoS ONE **1**, e12 (2006). https://doi.org/10.1371/journal.pone.0000012
4. Nokes, D., Swinton, J.: Vaccination in pulses: a strategy for global eradication of measles and polio? Trends Microbiol. **5**, 14–19 (1997). https://doi.org/10.1016/S0966-842X(97)81769-6
5. CDC: Case Investigation and Contact Tracing : Part of a Multipronged Approach to Fight the COVID-19 Pandemic [WWW Document]. Center for Disease Control and Prevention (CDC) (2020). https://www.cdc.gov/coronavirus/2019-ncov/php/principles-contact-tracing.html. Accessed 5 Sep 2020
6. Hethcote, H.W., Yorke, J.A.: Gonorrhea Transmission Dynamics and Control. Springer (2014)
7. CDC: Contact Tracing—Get and Keep America Open: Supporting states, tribes, localities, and territories. Centers for Disease Control and Prevention (CDC) (2020).
8. Faye, O., Boëlle, P.-Y., Heleze, E., Faye, O., Loucoubar, C., Magassouba, N., Soropogui, B., Keita, S., Gakou, T., Bah, E.H.I., Koivogui, L., Sall, A.A., Cauchemez, S.: Chains of transmission and control of Ebola virus disease in Conakry, Guinea, in 2014: an observational study. Lancet Infect. Dis. **15**, 320–326 (2015). https://doi.org/10.1016/S1473-3099(14)71075-8
9. Anglemyer, A., Moore, T.H., Parker, L., Chambers, T., Grady, A., Chiu, K., Parry, M., Wilczynska, M., Flemyng, E., Bero, L.: Digital contact tracing technologies in epidemics: a rapid review. Cochrane Database Syst. Rev. (2020). https://doi.org/10.1002/14651858.CD013699
10. Kretzschmar, M.E., Rozhnova, G., van Boven, M.: Isolation and contact tracing can tip the scale to containment of COVID-19 in populations with social distancing. Front. Phys. **8**, 622485 (2021). https://doi.org/10.3389/fphy.2020.622485
11. WHO: Situation Report - 72, Coronavirus disease 2019 (COVID-19) (2020)
12. Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D., Fraser, C.: Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. Science **368**, eabb6936 (2020). https://doi.org/10.1126/science.abb6936
13. COVID-19 Coronavirus Pandemic [WWW Document]: worldometer (2020). https://www.worldometers.info/coronavirus/?utm_campaign=homeAdvegas1?%22. Accessed 28 Nov 2020
14. Johansson, J.K., Niiranen, T.J., Puukka, P.J., Jula, A.M.: Prognostic value of the variability in home-measured blood pressure and heart rate: the Finn-home study. Hypertension **59**, 212–218 (2012). https://doi.org/10.1161/HYPERTENSIONAHA.111.178657
15. Skoll, D., Miller, J.C., Saxon, L.A.: COVID-19 testing and infection surveillance: is a combined digital contact-tracing and mass-testing solution feasible in the United States? Cardiovascul. Dig. Health J. **1**, 149–159 (2020). https://doi.org/10.1016/j.cvdhj.2020.09.004
16. Novel Coronavirus—China: Emergencies preparedness, response. World Health Organization (2020)
17. Abouzid, M., El-Sherif, D.M., Eltewacy, N.K., Dahman, N.B.H., Okasha, S.A., Ghozy, S., Islam, S.M.S.: Influence of COVID-19 on lifestyle behaviors in the Middle East and North Africa Region: a survey of 5896 individuals. J. Transl. Med. **19**, 1–11 (2021)
18. Ghozy, S., Abdelaal, A., Shah, J., Parker, K.E., Islam, S.M.S.: COVID-19 and physical inactivity: Teetering on the edge of a deadlier pandemic? J. Glob. Health **11** (2021)

19. Rahman, M.A., Hoque, N., Alif, S.M., Salehin, M., Islam, S.M.S., Banik, B., Sharif, A., Nazim, N.B., Sultana, F., Cross, W.: Factors associated with psychological distress, fear and coping strategies during the COVID-19 pandemic in Australia. Glob. Health **16**, 1–15 (2020)
20. Rahman, M.A., Islam, S.M.S., Tungpunkom, P., Sultana, F., Alif, S.M., Banik, B., Salehin, M., Joseph, B., Lam, L., Watts, M.C.: COVID-19: factors associated with psychological distress, fear, and coping strategies among community members across 17 countries. Glob. Health **17**, 1–19 (2021)
21. Ullah, I., Islam, M., Ali, S., Jamil, H., Tahir, M.J., Arsh, A., Shah, J., Islam, S.M.S.: Insufficient physical activity and sedentary behaviors among medical students during the COVID-19 lockdown: findings from a cross-sectional study in Pakistan. Int. J. Environ. Res. Public Health **18**, 10257 (2021)
22. Alizadehsani, R., Alizadeh Sani, Z., Behjati, M., Roshanzamir, Z., Hussain, S., Abedini, N., Hasanzadeh, F., Khosravi, A., Shoeibi, A., Roshanzamir, M.: Risk factors prediction, clinical outcomes, and mortality in COVID-19 patients. J. Med. Virol. **93**, 2307–2320 (2021)
23. Micah, A.E., Cogswell, I.E., Cunningham, B., Ezoe, S., Harle, A.C., Maddison, E.R., McCracken, D., Nomura, S., Simpson, K.E., Stutzman, H.N.: Tracking development assistance for health and for COVID-19: a review of development assistance, government, out-of-pocket, and other private spending on health for 204 countries and territories, 1990–2050. The Lancet (2021)
24. Rabbani, G., Shariful Islam, S.M., Rahman, M.A., Amin, N., Marzan, B., Robin, R.C., Alif, S.M.: Pre-existing COPD is associated with an increased risk of mortality and severity in COVID-19: a rapid systematic review and meta-analysis. Expert Rev. Respir. Med. **15**, 705–716 (2021)
25. Rahman, Md. A., Halder, H.R., Islam, S.M.S.,: Effects of COVID-19 on maternal institutional delivery: Fear of a rise in maternal mortality. J. Glob. Health **11** (2021)
26. Hajjar, L.A., da Costa, I.B.S., S., Rizk, S.I., Biselli, B., Gomes, B.R., Bittar, C.S., de Oliveira, G.Q., de Almeida, J.P., de Oliveira Bello, M.V., Garzillo, C., Leme, A.C., Elena, M., Val, F., de Almeida Lopes, M., Lacerda, M.V.G., Ramires, J.A.F., Kalil Filho, R., Teboul, J.-L., Landoni, G.,: Intensive care management of patients with COVID-19: a practical approach. Ann. Intensive Care **11**, 36 (2021). https://doi.org/10.1186/s13613-021-00820-w
27. Cohen, J., van der Rodgers, Y., M.,: Contributing factors to personal protective equipment shortages during the COVID-19 pandemic. Prev. Med. **141**, 106263 (2020). https://doi.org/10.1016/j.ypmed.2020.106263
28. Golechha, M.: India should ramp up its emergency medicine and critical care infrastructure to combat COVID-19. Postgrad. Med. J. **97**, 266 (2021). https://doi.org/10.1136/postgradmedj-2020-138249
29. Block, P., Hoffman, M., Raabe, I.J., Dowd, J.B., Rahal, C., Kashyap, R., Mills, M.C.: Social network-based distancing strategies to flatten the COVID-19 curve in a post-lockdown world. Nat. Hum. Behav. **4**, 588–596 (2020). https://doi.org/10.1038/s41562-020-0898-6
30. Downey: Total cost of NHS contact-tracing app set to top £35 million [WWW Document]. Digitalhealth (2020). https://www.digitalhealth.net/2020/09/total-cost-of-nhs-contact-tracing-app-set-to-top-35-million/. Accessed 9 May 2021
31. Lovejoy, B.: Germany's contact tracing app using Apple API launches; somehow cost $22.7M. 9to5Mac (2020)
32. Kumar, A.: Resurgence of COVID-19 in India: A Tale of Six Unlearnt Lessons. The Wire (2021)
33. Fitzsimons, J.K., Mantri, A., Pisarczyk, R., Rainforth, T., Zhao, Z.: A note on blind contact tracing at scale with applications to the COVID-19 pandemic. In: Proceedings of the 15th International Conference on Availability, Reliability and Security. Presented at the ARES 2020: The 15th International Conference on Availability, Reliability and Security, ACM, Virtual Event Ireland, pp. 1–6 (2020). https://doi.org/10.1145/3407023.3409204
34. Clark, E., Chiao, E.Y., Amirian, E.S.: Why contact tracing efforts have failed to curb coronavirus disease 2019 (COVID-19) transmission in much of the United States. Clin. Infect. Diseases ciaa1155 (2020). https://doi.org/10.1093/cid/ciaa1155

35. Crouch, H.: Google and Apple release their contact-tracing software [WWW Document]. Difitalhealth (2020). https://www.digitalhealth.net/2020/05/google-apple-contact-tracing-software-release/. Accessed 9 May 2021
36. Park, S., Choi, G.J., Ko, H.: Information technology-based tracing strategy in response to COVID-19 in South Korea—privacy controversies. JAMA **323**, 2129 (2020). https://doi.org/10.1001/jama.2020.6602
37. Bassi, A., Arfin, S., John, O., Jha, V.: An overview of mobile applications (apps) to support the coronavirus disease 2019 response in India. Indian J. Med. Res. **151**, 468 (2020). https://doi.org/10.4103/ijmr.IJMR_1200_20
38. Rasker, R., Dhillon, R., Kapa, S., Pahwa, D., Fatlgas, R., Sinha, L., Prasad, A., Singh, A., Nuzzo, A., Iyer, R., Sharma, V.: Comparing manual contact tracing and digital contact advice. arxiv.org, Computer and Society (n.d.).
39. Sinha, P., Paterson, A.E.: Contact tracing: can "Big tech" come to the rescue, and if so, at what cost? EClinicalMedicine **24**, 100412 (2020). https://doi.org/10.1016/j.eclinm.2020.100412
40. Osborne, C.: Proposed government coronavirus tracking app falls at the first hurdle due to data breach. Coronavirus: business and technology in a pandemic (2020)
41. Lucivero, F., Hallowell, N., Johnson, S., Prainsack, B., Samuel, G., Sharon, T.: COVID-19 and contact tracing apps: ethical challenges for a social experiment on a global scale. J. Bioeth. Inq. **17**, 835–839 (2020). https://doi.org/10.1007/s11673-020-10016-9
42. Azad, M.A., Arshad, J., Akmal, S.M.A., Riaz, F., Abdullah, S., Imran, M., Ahmad, F.: A first look at privacy analysis of COVID-19 contact tracing mobile applications. IEEE Internet Things J. **1–1**,(2020). https://doi.org/10.1109/JIOT.2020.3024180
43. The Washington Post: Washington Post-University of Maryland national poll, April 21–26, 2020. The Washington Post (2020)
44. Garza, A.D.L.: Contact Tracing Apps Were Big Tech's Best Idea for Fighting COVID-19. Why Haven't They Helped? TIME (2020)
45. Hosein, G.: Privacy and Developing Countries. Office of the Privacy Commissioner of Canada (2011)
46. O'Dea, S.: Number of smartphone users worldwide from 2016 to 2023, Technology & Telecommunications. Statista (2020)
47. Bradshaw, T.: 2 billion phones cannot use Google and Apple contact-tracing tech [WWW Document]. ars Technica (2020). https://www.arstechnica.com/tech-policy/2020/04/2-billion-phones-cannot-use-google-and-apple-contract-tracing-tech/. Accessed 5 Sep 2021)
48. Sapiezynski, P., Pruessing, J., Sekara, V.: The Fallibility of Contact-Tracing Apps (2020). arXiv:2005.11297
49. Elliot, R.: Mobile Phone Penetration Throughout Sub-Saharan Africa. GeoPoll (2019)
50. Yoon, J.S.: Smartphone penetration rate as share of the population in South Korea from 2015 to 2025, Telecommunications. South Korea (2020)
51. Taylor, K., Silver, L.: Smartphone Owndership Is Growing Rapidly Around the World, but Not Always Equally. Pew Research Center (2019)
52. Bogdan-Martin, D.: Measuring digital development: Facts & figures 2019. ITUNews (2019)
53. Turner, A.: How many smartphones are in the world? [WWW Document]. bankmycell (2020). https://www.bankmycell.com/blog/how-many-phones-are-in-the-world. Accessed 3 July 2020
54. BTRC: Internet Subscribers Bangladesh [WWW Document]. BTRC (2020). http://www.btrc.gov.bd/content/internet-subscribers-bangladesh-may-2020. Accessed 7 Mar 2020
55. Rowntree, O.: The Mobile Gender Gap Report 2019, GSMA Connected Women. GSMA (2019)
56. World Bank: Rural population (% of total population)—Bangladesh [WWW Document]. World Bank (2018). https://www.data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=BD. Accessed 9 May 2020
57. Golechha, M.: COVID-19 containment in Asia's largest Urban Slum Dharavi-Mumbai, India: lessons for policymakers globally. J. Urban Health **97**, 796–801 (2020). https://doi.org/10.1007/s11524-020-00474-2

58. Alsdurf, H., Bengio, Y., Deleu, T., Gupta, P., Ippolito, D., Janda, R., Jarvie, M., Kolody, T., Krastev, S., Maharaj, T.: Covi white paper (2020). arXiv:2005.08502
59. Chowdhury, M.J.M., Ferdous, M.S., Biswas, K., Chowdhury, N., Muthukkumarasamy, V.: COVID-19 contact tracing: challenges and future directions. IEEE Access **8**, 225703–225729 (2020). https://doi.org/10.1109/ACCESS.2020.3036718
60. Zhao, Q., Wen, H., Lin, Z., Xuan, D., Shroff, N.: On the accuracy of measured proximity of bluetooth-based contact tracing apps. In: Park, N., Sun, K., Foresti, S., Butler, K., Saxena, N. (Eds.), Security and Privacy in Communication Networks, Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. Springer International Publishing, Cham, pp. 49–60 (2020). https://doi.org/10.1007/978-3-030-63086-7_4
61. Google Play Store [WWW Document] (2021). https://www.play.google.com/store/apps?hl=en&gl=US. Accessed 9 May 5 2021
62. Sekara, V., Lehmann, S.: The strength of friendship ties in proximity sensor data. PLoS ONE **9**, e100915 (2014). https://doi.org/10.1371/journal.pone.0100915
63. Li, J., Guo, X.: Global deployment mappings and challenges of contact-tracing apps for COVID-19. SSRN J. (2020). https://doi.org/10.2139/ssrn.3609516
64. Foxe, K.: Covid-19 app: 150,000 uninstalled app after August battery issue [WWW Document]. Irish Examiner (2020). https://www.irishexaminer.com/news/arid-40058456.html. Accessed 9 May 2020
65. Vonau, M.: COVID-19 tracing apps may fail to notify exposed users due to aggressive OEM battery saving measures [WWW Document]. Android Police (2020). https://www.androidpolice.com/2020/07/24/covid-19-tracing-apps-may-fail-to-notify-exposed-users-due-to-aggressive-oem-battery-saving-measures/
66. Lu, J., Gu, J., Li, K., Xu, C., Su, W., Lai, Z., Zhou, D., Yu, C., Xu, B., Yang, Z.: COVID-19 outbreak associated with air conditioning in restaurant, Guangzhou, China, 2020. Emerg. Infect. Dis. **26**, 1628–1631 (2020). https://doi.org/10.3201/eid2607.200764
67. Chong, C.: About 1 million people have downloaded Trace Together app, but more need to do so for it to be effective: Lawrence Wong [WWW Document]. The Straits Times (2020). https://www.straitstimes.com/singapore/about-one-million-people-have-downloaded-the-tracetogether-app-but-more-need-to-do-so-for
68. Meixner, S.: How many people have downloaded the COVIDSafe app and how central has it been to Australia's coronavirus response? News (2020)
69. Olsen, S.J.: Stop infections on the iPhone only works properly when the app is open [WWW Document]. TEK.NO (2020). https://www.tek.no/nyheter/nyhet/i/Vb8vep/smittestopp-paa-iphone-fungerer-bare-skikkelig-naar-appen-er-aapen. Accessed 9 May 5 2021
70. statista: Adoption of government endorsed COVID-19 contact tracing apps in selected countries as of July 2020, Mobile Internet & Apps. Statista (2020)
71. Aarogya Setu [WWW Document] (2021). https://www.aarogyasetu.gov.in/. Accessed 5 Aug 2021
72. Satija, R.: Aarogya Setu is fastest app in the world to reach 50 million users despite privacy concerns [WWW Document] (2020). https://www.theprint.in/tech/aarogya-setu-is-fastest-app-in-the-world-to-reach-50-million-users-despite-privacy-concerns/403025/. Accessed 9 May 2021
73. Perrigo, B.: A New, More Contagious COVID-19 Strain Has Been Reported in the U.K. Is It Headed for the U.S. TIME (2020)
74. Du, P.-Y., Zhang, N., Ebrahimi, M., Samtani, S., Lazarine, B., Arnold, N., Dunn, R., Suntwal, S., Angeles, G., Schweitzer, R., Chen, H.: Identifying, collecting, and presenting hacker community data: forums, IRC, carding shops, and DNMs. In: 2018 IEEE International Conference on Intelligence and Security Informatics (ISI). Presented at the 2018 IEEE International Conference on Intelligence and Security Informatics (ISI), IEEE, Miami, FL, pp. 70–75 (2018). https://doi.org/10.1109/ISI.2018.8587327
75. Watson, C., Cicero, A., Blumenstock, J., Fraser, M.: A National Plan to Enable Comprehensive COVID-19 Case Finding and Contact Tracing in the US. Johns Hopkins Bloomberg School of Public Health, United States (2020)

76. Cheng, H.-Y., Jian, S.-W., Liu, D.-P., Ng, T.-C., Huang, W.-T., Lin, H.-H., for the Taiwan COVID-19 Outbreak Investigation Team: Contact tracing assessment of COVID-19 transmission dynamics in Taiwan and risk at different exposure periods before and after symptom Onset. JAMA Intern Med **180**, 1156 (2020). https://doi.org/10.1001/jamainternmed.2020.2020
77. Steinbrook, R.: Contact tracing, testing, and control of COVID-19—Learning from Taiwan. JAMA Intern. Med. **180**, 1163 (2020). https://doi.org/10.1001/jamainternmed.2020.2072
78. Peet, C.: Out of control: Brazil's COVID surge sparks regional fears [WWW Document]. Aljazeera (2021). https://www.aljazeera.com/news/2021/4/10/out-of-control-brazils-covid-surge-sparks-regional-fears. Accessed 9 May 2021
79. The Economist: India is struggling with a catastrophic second wave. The Economist (2021)
80. Troncoso, C., Payer, M., Hubaux, J.-P., Salathé, M., Larus, J., Bugnion, E., Lueks, W., Stadler, T., Pyrgelis, A., Antonioli, D.: Decentralized privacy-preserving proximity tracing (2020). arXiv:2005.12273
81. Council of Europe: Joint statement on contact tracing: date 19th April 2020
82. Magklaras, G., López-Bojórquez, L.N.: A review of information security aspects of the emerging COVID-19 contact tracing mobile phone applications. In: International Symposium on Human Aspects of Information Security and Assurance. Springer, pp. 30–44 (2020)
83. Ahmed, N., Michelin, R.A., Xue, W., Ruj, S., Malaney, R., Kanhere, S.S., Seneviratne, A., Hu, W., Janicke, H., Jha, S.K.: A survey of COVID-19 contact tracing apps. IEEE Access **8**, 134577–134601 (2020). https://doi.org/10.1109/ACCESS.2020.3010226
84. de Montjoye, Y.-A., Ramadorai, T., Valletti, T., Walther, A.: Privacy, adoption, and truthful reporting: a simple theory of contact tracing applications. Econ. Lett. **198**, 109676 (2021). https://doi.org/10.1016/j.econlet.2020.109676
85. Williams, S.N., Armitage, C.J., Tampe, T., Dienes, K.: Public attitudes towards COVID-19 contact tracing apps: a UK-based focus group study (preprint). Public Glob. Health (2020). https://doi.org/10.1101/2020.05.14.20102269
86. Trang, S., Trenz, M., Weiger, W.H., Tarafdar, M., Cheung, C.M.K.: One app to trace them all? Examining app specifications for mass acceptance of contact-tracing apps. Eur. J. Inf. Syst. **29**, 415–428 (2020). https://doi.org/10.1080/0960085X.2020.1784046
87. Mallapaty, S.: Can COVID vaccines stop transmission? Scientists race to find answers. Nature d41586-021–00450-z (2021). https://doi.org/10.1038/d41586-021-00450-z
88. Khurshid, A.: Applying blockchain technology to address the crisis of trust during the COVID-19 pandemic. JMIR Med. Inform. **8**, e20477 (2020). https://doi.org/10.2196/20477
89. Xu, H., Zhang, L., Onireti, O., Fang, Y., Buchanan, W.J., Imran, M.A.: BeepTrace: blockchain-enabled privacy-preserving contact tracing for COVID-19 pandemic and beyond. IEEE Internet Things J. **8**, 3915–3929 (2021). https://doi.org/10.1109/JIOT.2020.3025953
90. Moses, J.C., Adibi, S., Shariful Islam, S.M., Wickramasinghe, N., Nguyen, L.: Application of Smartphone Technologies in Disease Monitoring: A Systematic Review, p. 889. Multidisciplinary Digital Publishing Institute, Presented at the Healthcare (2021)
91. Sharif, A., Botlero, R., Hoque, N., Alif, S.M., Karim, M.N., Islam, S.M.S.: A pragmatic approach to COVID-19 vaccine passport. BMJ Glob. Health **6**, e006956 (2021)
92. Aktar, S., Ahamad, M.M., Rashed-Al-Mahfuz, M., Azad, A., Uddin, S., Kamal, A., Alyami, S.A., Lin, P.-I., Islam, S.M.S., Quinn, J.M.: Machine learning approach to predicting COVID-19 disease severity based on clinical blood test data: statistical analysis and model development. JMIR Med. Inform. **9**, e25884 (2021)
93. Frost, D., Mahmud, M., Kaiser, M.S., Musoke, D., Henry, P., Islam, S.: Innovative Approaches to Strengthening Health Systems in Low-and Middle-Income countries: Current Models, Developments, and Challenges. Health Policy and Technology (2021)
94. Khozeimeh, F., Sharifrazi, D., Izadi, N.H., Joloudari, J.H., Shoeibi, A., Alizadehsani, R., Gorriz, J.M., Hussain, S., Sani, Z.A., Moosaei, H.: Combining a convolutional neural network with autoencoders to predict the survival chance of COVID-19 patients. Sci. Rep. **11**, 1–18 (2021)

95. Rashed-Al-Mahfuz, M., Moni, M.A., Lio, P., Islam, S.M.S., Berkovsky, S., Khushi, M., Quinn, J.M.: Deep convolutional neural networks based ECG beats classification to diagnose cardiovascular conditions. Biomed. Eng. Lett. **11**, 147–162 (2021)
96. Satu, M., Howlader, K.C., Mahmud, M., Kaiser, M.S., Shariful Islam, S.M., Quinn, J.M., Alyami, S.A., Moni, M.A.: Short-term prediction of COVID-19 cases using machine learning models. Appl. Sci. **11**, 4266 (2021)
97. Soron, T.R., Islam, S.M.S., Ahmed, H.U., Ahmed, S.I.: The hope and hype of telepsychiatry during the COVID-19 pandemic. Lancet Psych. **7**, e50 (2020)
98. Idrees, S.M., Nowostawski, M., Jameel, R.: Blockchain-based digital contact tracing apps for COVID-19 pandemic management: issues, challenges, solutions, and future directions. JMIR Med. Inform. **9**, e25245 (2021). https://doi.org/10.2196/25245
99. Siam, Z.S., Md., Arifuzzaman, Ahmed, Md.S., Khan, F.A., Rashid, Md.H., Islam, Md.S.: Dynamics of COVID-19 transmission in Dhaka and Chittagong: two business hubs of Bangladesh. Clin. Epidemiol. Glob. Health **10**, 100684 (2021). https://doi.org/10.1016/j.cegh.2020.100684
100. Abboah-Offei, M., Salifu, Y., Adewale, B., Bayuo, J., Ofosu-Poku, R., Opare-Lokko, E.B.A.: A rapid review of the use of face mask in preventing the spread of COVID-19. Int. J. Nurs. Stud. Adv. **3**, 100013 (2021). https://doi.org/10.1016/j.ijnsa.2020.100013
101. Liao, M., Liu, H., Wang, X., Hu, X., Huang, Y., Liu, X., Brenan, K., Mecha, J., Nirmalan, M., Lu, J.R.: A technical review of face mask wearing in preventing respiratory COVID-19 transmission. Curr. Opin. Colloid Interface Sci. **52**, 101417 (2021). https://doi.org/10.1016/j.cocis.2021.101417

A Re-configurable Software-Hardware CNN Framework for Automatic Detection of Respiratory Symptoms

Hasib-Al Rashid, Haoran Ren, Arnab Neelim Mazumder, Mohammad M. Sajadi, and Tinoosh Mohsenin

Abstract Detection of respiratory symptoms has long been an area of extensive research to expedite the process of machine aided diagnosis for various respiratory conditions. This chapter attempts to address the early diagnosis of respiratory conditions using low power scalable software and hardware involving end-to-end convolutional neural networks (CNNs). We propose RespiratorNet, a scalable multimodal CNN software hardware architecture that can take audio recordings, speech information, and other sensor modalities belonging to patient demographic or symptom information as input to classify different respiratory symptoms. We analyze four different publicly available datasets and use them as case studies as part of our experiment to classify respiratory symptoms. With regards to fitting the network architecture to the hardware framework, we perform windowing, low bit-width quantization, and hyperparameter optimization on the software side. As per our analysis, detection accuracy goes up by 5% when patient demographic information is included in the network architecture. The hardware prototype is designed using Verilog HDL on Xilinx Artix-7 100t FPGA with hardware scalability extending to accommodate different numbers of processing engines for parallel processing. The proposed hardware implementation has a low power consumption of only 245 mW and achieves an energy efficiency of 7.3 GOPS/W which is 4.3 better than the state-of the-art accelerator implementations. In addition, RespiratorNet TensorFlow model is implemented

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on NVIDIA Jetson TX2 SoC (CPU+GPU) and compared to TX2 single-core CPU and GPU implementations to provide scalability in terms of off-the-shelf platform implementations.

Keywords Multimodal CNN · Scalable respiratory symptoms detection · Low power embedded · Audio detection · FPGA

1 Introduction

Most of the people are not that much of conscious with breathing and respiratory health and overlook the fact that their lungs are important organs that are susceptible to infections and damages. Acute respiratory infections, as well as chronic respiratory illnesses such as asthma, chronic obstructive pulmonary disease, and lung cancer, are examples of respiratory diseases. Because the symptoms of respiratory diseases are frequently quite similar, this may lead to confusion and misinterpretation. Making a prompt and correct diagnosis is critical for the treatment of the respiratory related diseases. This may have disastrous effects if the virus spreads further, especially during pandemics like the COVID-19 pandemic. The outbreak of highly contagious COVID-19 and other respiratory infections have placed tremendous strain on the healthcare system. COVID19 causes symptoms such as dry cough, fever, fatigue, dyspnea, and shortness of breath that vary in severity at various stages of the development of the disease and correspond differently with certain races, genders, and age groups. In combination with dry cough, fever was registered by over 70% of COVID-19 confirmed patients [1]. Clinical case studies indicate that the young population is less likely to experience related symptoms of COVID-19 in contrast with the elderly, which is the most affected group [2]. However, as mentioned 5earlier, these respiratory related symptoms are not unique for only present threat COVID-19. A wide range of chronic and infectious diseases include pulmonary disorders and they develop respiratory symptoms due to the essential organ that they affect, the lung, whose auditory signals detected by various diagnostic instruments are among the first to be studied by a medical expert. As a result, establishing a diagnostic differentiator is critical for determining a fast and accurate diagnosis of respiratory symptoms and taking necessary measures.

Cough is a common sign of respiratory illnesses [3]. Cough is a common lung illness sign and a normal human defensive mechanism to protect the respiratory system Korpáš and Tomori [4]. During treatment, analyzing the cough sound may provide useful information about the coughing pathophysiological processes that lead to specific cough patterns Korpáš et al. [5]. Changes in cough sound are regarded as a crucial indication of the progression of respiratory illness and the efficacy of treatment Korpáš et al. [5]. Because coughs are often seasonal, a cough classifier or detector must have a very low false alarm rate to be regarded clinically trustworthy. Furthermore, this system must be very sensitive to variations in cough noises in order to identify any unusual occurrence [6].

Our previous works show promising results on detecting various respiratory diseases from cough sounds and respiratory sounds [7–9]. This chapter introduces RespiratorNet, a scalable and multimodal deep Convolutional Neural Network (DCNN) model running on tiny processors (e.g. tiny FPGAs and processors on cell-phones and tablets) to assess patients similar to what doctors do at triage and telemedicine, using passively recorded cough audio, speech, and self-entry information (such as age, gender and fever). The proposed software and hardware framework is scalable and can potentially have a great impact by bringing proactive healthcare to users' finger tips and to estimate the necessity of whether they need to attend clinics and have themselves further examined with the use of more specialized test-kits or facilities. This chapter is extensive extension from our previous work [8]. The main contributions of this work include:

- Propose RespiratorNet, a scalable multimodal CNN software hardware framework that can take audio recordings and speech recordings from individuals along with demographic information and other entries of the subject and be configured for classifying respiratory symptoms. RespiratorNet allows the software and hardware to quickly integrate new sensors data that are customized to various types of scenarios.
- Perform input audio window size tuning, network architecture optimization and extreme bitwidth quantization, with the goal of reducing computation complexity and memory size for low power hardware implementation while meeting the accuracy requirements.
- Design a parameterized and flexible hardware in verilog HDL for different input modalities and numbers of processing engines (PE) that replicate the RespiratorNet architecture for low power deployment.
- A comprehensive FPGA hardware implementation and benchmarking of the proposed work with different three case studies, and comparisons with the state-ofthe-art FPGA implementation results.
- Implement the TensorFlow model of RespiratorNet on embedded Nvidia Jetson TX2 board and measure its implementation characteristics for various CPU and GPU configurations.

2 Related Work

Audio based medical diagnosis has recently become an active area of research with the advancement of different machine learning and deep learning algorithms. Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) Networks have shown impressive performance in image and time-series classification tasks [10–12] as well as audio recognition tasks [9, 13, 14]. Using chest-mounted sensors, Amoh and Odame [15] used both DCNNs and recurrent neural networks (RNNs) to classify cough sound. Deep learning was used to detect sleep apnea in Nakano et al. [16]. DCNNs showed promising performance in the heart sound classification in Ryu et al. [17]. Lung sounds were classified using DCNN in Aykanat et al. [18] and RNN

[19]. Although the reported accuracy is quite high, these researches were done on unpublished data set which limit the reproducibility and further improvement of the work on this domain. The 2017 International Conference on Biomedical Health Informatics (ICBHI) [20] presented a benchmark respiratory audio data set to promote research into the classification of respiratory sound systems. Since then, researchers proposed various algorithms [21–24] using different deep learning techniques to classify respiratory cycle anomalies such as the precise locations of wheezes and crackles within the cycle of each respiratory sound recording. That dataset helped the researchers to propose a number of algorithms to identify respiratory cycling irregularities such as the exact position of the wheezes and crackle within the cycle of every sound recording in the respiratory system. Acharya and Basu [25] proposed Log quantized deep CNN-RNN based model for respiratory sound classification for memory limited wearable devices. Recently, a research group from MIT already showed Covid-19 diagnosis using cough recording with high accuracy Laguarta et al. [26]. Two different datasets [27, 28] were published to classify multiple environmental sound which include cough sounds among the other classes. Recently, a group from EPFL published one of the biggest crowd sourced cough datasets [29]. These dataset help researchers to address audio classification based health monitoring systems which is in demand now-a-days due to Covid-19 pandemic.

3 RespiratorNet Framework

The high level overview of the proposed RespiratorNet framework is presented in Figure 1. RespiratorNet can take any kind of audio recording from the user and classify accordingly. RespiratorNet can also process human speech and classify whether there is any sign of shortness of breath in the speech. Moreover, to fine tune the classification accuracy, RespiratorNet can take numeric information as input related to demographic or symptoms vectors. We evaluated RespiratorNet with human cough sounds, recorded speech, and respiratory sounds integrated with demographic information which is explained in the following section. The detailed architecture of the RespiratorNet framework is presented in Fig. 2. As the input is in the form of audio recordings, it is divided into window frames to extract features, since the right windows to distinguish between static and continuous signals are crucial. Windowing involves first standardizing the independent variables and then creating sliding T windows with S growing over the results. If the channels are referred by M in the multimodal signals, then window images of shape 1T M are created with a label assigned to each window image as the label of the current time step. As a result, a window image at location Tt has previous states for each data point from $(t\ T + 1)$ … t where t is represented as the timestep. Then the window frames are forwarded into the CNN layers for necessary feature extraction and classification.

Our CNN layers are flexible in terms of number of layers. We can decide particular number of CNN layers based on the evaluation case studies. To extract the correlation between the one-dimensional audio signals, we used one-dimensional CNN layers in

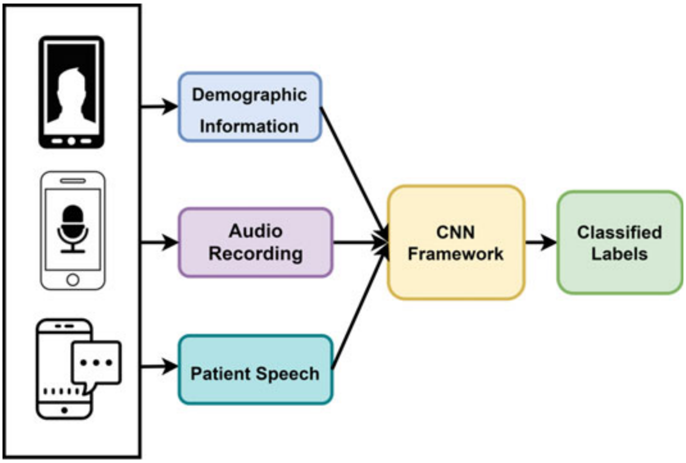

Fig. 1 The proposed multimodal *RespiratorNet* framework to classify respiratory symptoms. Some of the input information is auditory, such as the sound and frequency of coughing and speech that can detect patient's shortness of breath. Other input data can be sensed or entered manually such as demographic information. *RespiratorNet* is flexible and scalable in the sense that it allows the device to quickly integrate new sensors data that are customized to various types of scenarios, such as home appointments, hospital visits or even identification of symptoms in public settings with non-contact sensors

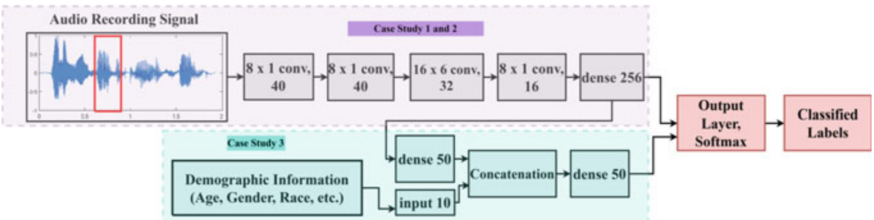

Fig. 2 The detailed architecture of the proposed flexible *RespiratorNet* in which end-to-end CNN is implemented that can be used for cough detection, dyspnea detection, and respiratory sound detection with/without the integration of other input vectors such as demographic information. The input and computation will differ according to the audio window size selected

the beginning of the model. The feature map size reduction is done by striding in the CNN layers. When we get the required small feature map size, the output is flattened and then forwarded to a number of fully connected layers to isolate sufficient window frame information with interconnections between nodes. At the end, the output is seen in the form of the probability distribution of the last fully layer with Softmax activation function.

In previous work, authors showed that if the domain specific knowledge is concatenated with the deep learning model, it improves the model accuracy. Based on this intuition, we have given flexibility to our model to process numeric information in the form of input vectors in parallel to the feature extraction. After the audio processing with the CNN layers, these input vectors containing numeric data is concatenated with the flattened output from the convolution framework of the classification model. This concatenated output is further processed through the fully connected layers to finalize the output label.

4 Experimental Results and Analysis

In this section, RespiratorNet is evaluated using three respiratory symptoms bearing case studies including *Cough detection, Dyspnea Detection and Detection of Respiratory Sound with Demographic Information* and in depth analysis and experimental results are provided.

4.1 Case Study 1: Cough Detection

We evaluated RespiratorNet for cough detection on three different datasets: ESC-50 Piczak [28], FSD Kaggle2018 [27], and Coughvid [29].

ESC-50 The ESC-50 dataset contains a total of 2,000 audio recordings of normal environmental sounds. It has 50 equally distributed classes including "coughing", so that each class has 40 audio recordings. All the audio recordings are 5 s in length, and are stored as single-channel audio waveform files at 44.1 kHz sampling rate. The dataset is originally divided into 5 folds with 400 audio recordings per fold. For each cross-validation round, we use 3 folds as train set, onefold as validate set, and onefold as test set.

Input sound duration is a key factor here to better distinguish sounds across the 50 classes. During preprocessing, we first load each audio recording with the default 44.1 kHz sampling rate and apply initial audio-wise regularization to the range of -1 to 1. Next, we crop the audio recording into windows, and discard silent windows if the window-wise maximum amplitude is less than a certain threshold. Each extract window has the same label as the audio recording which it is cropped from. At last, we apply the $(-1, 1)$ regularization again to each window individually.

We consider a window and its label as one instance of model input. However, since the sound of an audio recording may only exist in some of the extracted windows, we evaluate the predictions at audio recording level by probability-voting Piczak [28]. Specifically, we sum up all the softmax model outputs for every window extracted from one test audio recording, and make a prediction based on the summed-up output.

Models are trained using stochastic gradient descent (SGD) with a momentum of 0.6 for 100 epochs under the categorical cross-entropy criterion. The learning rate is initially defined as 0.01, and then it is decreased according to the convergence performance. For silent window removal, the amplitude threshold is 0.2. The window stride is always 0.25 s. We used Tensor-Flow Abadi et al. [30] for implementation of the models and associated methods and Librosa [31] for audio processing.

Figure 3a shows the accuracy results for this applications with respect to window size. As evident in Fig. 3a, all the experiments show similar performances on overall accuracy metric. As for the performance on cough detection, 1 s windows show good and balanced performance of extracting distinctive feature. Thus, a window size of 1 s is chosen for our implementation scenario.

FSDKaggle2018 Similar to ESC-50, the FSDKaggle2018 dataset contains 41 sound classes and cough is one of them. There are 11,073 audio recording samples, where each of the audio recordings is an uncompressed PCM 16 bit, 44.1 kHz, mono audio file. The dataset is separated into a train set with approximately 9.5 k samples and a test set with about 1.6k samples. The audio recordings spread unequally amongst the 41 classes for both the train set and the test set, with a similar category distribution

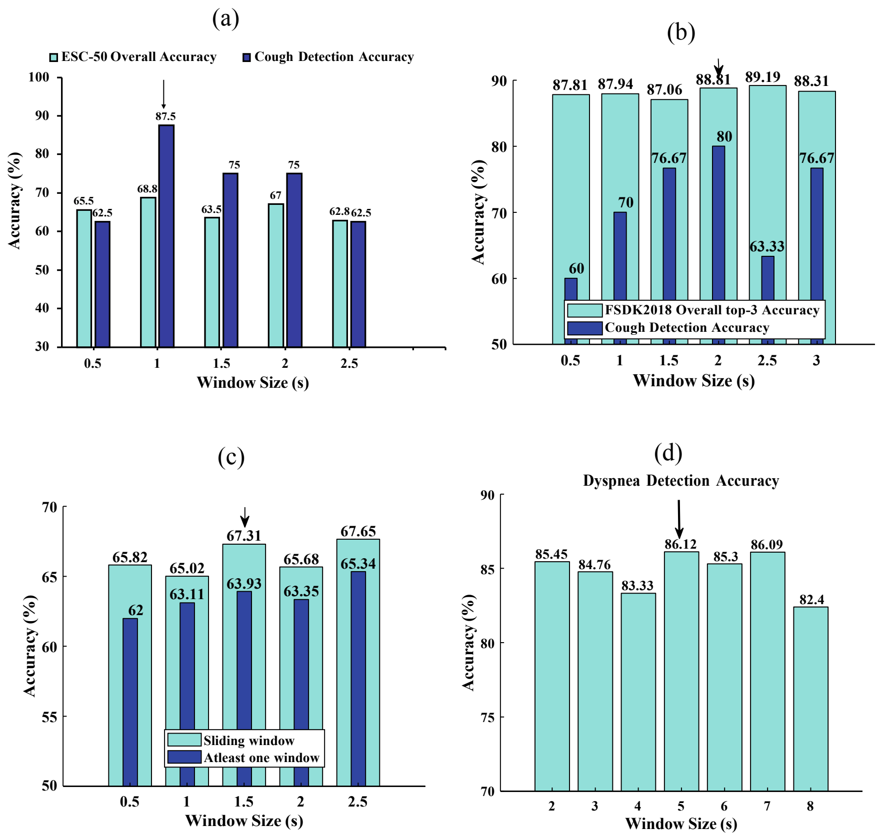

Fig. 3 Detection Accuracy with different window sizes for **a** ESC-50 cough detection, **b** FSDK2018 cough detection, **c** CoughVID cough detection and **d** Dyspnea detection. For window size experiments, padding is applied to 2D-convolutions

between them. Out of the 9.5k samples in the train set, 3.7k were listened by human participants and were annotated with ground truth label. The rest 5.8k samples have non-verified annotations with. The estimated accuracy of the non-verified annotations for each class is at least 65–70%. In contrast to the train set, the test set contains only manually-verified annotated samples.

To take fully use of both verified annotated audio recordings and non-verified annotated audio recordings, we handle them differently during training. Firstly, we train the model with verified annotated audio recordings only for initial convergence. Then, we use the entire train set to fine-tune the model. However, before each fine-tune round, we relabel the non-verified annotations. The new label is generated by mixing up the non-verified annotation and the prediction of the audio recording by the current model, with a mix-up ratio same as the ratio between the non-verified annotations quality and the test accuracy of the current model.

Same as our work on the ESC-50 dataset, we use 44.1 kHz sampling rate and same window extraction method. Meanwhile, we apply normalization and silence filtering during preprocessing and sliding window probability-voting at testing. The model hyper-parameters are also the same except training epoch number and learning rate decay. We consider the overall top-3 accuracy and recall score of the cough class as our metrics to assess the proposed architecture on cough detection. Figure 3b shows the accuracy results for this applications with respect to window size. As evident in Fig. 3b, all the experiments show similar performances on overall top-3 accuracy metric. As for the performance on cough detection, 2 s windows show good and balanced performance of extracting distinctive feature. Thus, a window size of 2 s is chosen for our implementation scenario.

CoughVID CoughVID is a crowdsourced dataset for machine learning researchers aiming to find the connections between COVID-19 diagnosis and cough sound features. It provides over 20,000 cough recordings donated by participants, as well as a wide range of other subjects such as ages, genders, geographic locations, and especially, COVID-19 statuses. As a quality check, the dataset organizers include a ML based cough detection result for each audio recording as well, which is a probability of how likely the audio recording contains at least one cough sound.

As an initial step of taking fully advantages of this dataset for COVID-19 research, we evaluate our previous work on cough detection with it. In details, we use models trained on the ESC-50 dataset to predict cough existence, and compare with an assumed ground truth based on the affiliated probability. We consider two cough existence prediction schemes here. For the first one, we predict the audio recording contains cough if cough class is among the top-5 predictions of the sliding-window probability-voting results. For the second one, if at least one window gives a cough prediction among the top-5 predictions, we consider the audio recording has cough. As recommended by the dataset organizer, the assumed ground truth labels are generated by whether the affiliated cough existence probability is greater than 80% or not. Figure 3c shows the results for both schemes by different input window sizes, in accuracy of exist and non-exist binary prediction.

4.2 Case Study 2: Dyspnea Detection

We also assess the efficiency of RespiratorNet on dyspnea detection, with a dataset collected from our participants. For each participant, we record two audio recordings. One is the sound of reading an article paragraph normally, and the other one is reading the same paragraph after some strenuous exercises, so that some gasp sounds would be included. We label the two audio recordings as normal and dyspnea accordingly. The recordings are recorded by various devices and then re-sampled at a sampling rate of 44.1 kHz. Each recording has a length between 30 and 60 s. After window extraction with different configurations, we could have about 3000 windows to be divided into train, validation, and test sets, while making sure that no window in the test set is overlapped with any window in the train set.

Most of the model configurations are the same as the previous work. One difference is that we do not apply silence filtering for this case study, due to the fact that audio recordings may include gasps. The other one is that we use window-wise prediction at testing, since we are doing a binary classification on the relatively small dataset. It is obvious from Fig. 3d that the window size of 5 s and 7 s works better for the model of dyspnea detection. The number of computation would be increased by a higher window size. We therefore chose to use the 5 s window for this application.

4.3 Case Study 3: Detection of Respiratory Sound with Demographic Information

In Sects. 4.1 and 4.2, we evaluate the performance of RespiratorNet only with auditory input. In this one, we also include demographic information. The dataset [32] we use for this case study comprises 920 recordings collected from 126 participants with annotations unequally disperse among 8 forms of respiratory conditions, including Upper Respiratory Tract Infection (URTI), Asthma, Chronic Obstructive Pulmonary Disease (COPD), Lower Respiratory Tract Infection (LRTI), Bronchiectasis, Pneumonia, and Bronchiolitis. The length of each recording varies from 10 to 90 sonds, often be controlled with 20 s samples.

While the majority of this dataset are COPD-diagnosed participants, by taking only audio recordings captured by Welch Allyn Meditron Master Elite Electronic Stethoscope, one of the four devices used for this dataset, we generate a random subset encompassing 63 participants. We split it into a semi-balanced train and a test set of 52 and 11 participants that include 5 types of pulmonary classes. In consequence, we eliminate Asthma, Pneumonia, and LRTI.

Each selected audio sample is cut into 5 s windows with a stride of 1 s for data augmentation. Therefore, about 1600 windows are generated from the total 2000s of the training dataset, and 368 windows are generated from the total 460 s testing data.

The selection of the 5 s window is empirically inferred from the experience varying from 1 to 10 s.

Table 1 Respiratory sound classification accuracy and model complexity with and without taking the demographic information into account

DCNN characteristics	Sensitivity (%)					Accuracy (%)
	URTI	Healthy	COPD	Bronchiec	Bronchiol	Test
Without demographic info	21	66	96	88	4	78
With demographic info	16	72	100	88	15	83 (+5%)

We performed a series of experiments, from audio input only, to merging the age group information with auditory signal. Table 1 contrasts the two sets of studies, suggesting that the COPD and healthy conditions are diagnosed with higher accuracy and resulting in a total test accuracy increased by 5% when the demographic information is taken into account.

5 Hardware Architecture Design

The hardware architecture must be built with special care for accurate processing and functionality in order to incorporate RespiratorNet for the detection of cough and dyspnea along with the classification of respiratory sounds with demographic or symptoms details. This applies to basic design needs such as parallel calculation and effective memory sharing. This architecture is also modeled mainly to comply with the latency requirement with a low area and utilization overhead. In order to achieve the required performance and power efficiency requirements, the hardware architecture thus implemented here is reconfigured to any number of filters, processing engines (PEs) and layers for any model.

5.1 FPGA Design Flow and Framework

The main blocks that dominate the logic flow and memory footprint in terms of computation and resources are explained below:

The **Convolution** module performs 1D and 2D convolution depending on the software architecture requirement. The control unit defines the functionality of the convolution by using the address generator to address the convolution process dynamically, involving stride and corner case scenarios. The **Fully Connected** module represents the functionality of the fully connected layers where all the neurons are connected to each other. The block is also guided to a matrix vector multiplication with proper addressing by the control unit and an address generator. The generated data are collected in the PE array. The **PE array** uses uses a multiplier and an adder with ReLu activation feature to duplicate the MAC process. This module also spreads the data into various arrays to allow parallel processing, depending on the number of PEs initialized in the parameters. All the necessary modules have been integrated in the **Top** module. Furthermore this block also maintains a logic flow and controls the data path to PE array, Convolution and the Fully connected modules. The demographic/numerical information used in the case study 3 is provided in **Symptoms/Demographic Vector** block. The numerical information shall be stored as an one dimensional vector which after processing, is concatenated to the feature map memory. The control unit supervises this concatenation process, while the state machine controls the layer flow after the concatenation.

The finite-state machine (FSM) controls the process flow and logic for convolutional and fully connected layer operation. The address generated through the layer functionality is sent to the on-chip Block RAM (BRAM) memory instantly where each of the memory locations has a data width of 8-bits. Consequently, the input data from the feature map passes through the multiply-accumulate unit inside the PE array, and the product of the computation is saved on the output memory through ReLu activation logic. The PE logic is implemented only through a pipeline of an adder, a multiplier, and an accumulator which saves resources. The PE array ensures parallel execution of the convolution setup as evident from the Fig. 4, where 8-bit values are read from the feature map memory but n 8 values are processed from weight memory for parallel operation where n is equal to the numbers of PEs in the array. The output from each PE continues storing these values until all values are received. As a result, the PE arrays are completely independent of each other in terms of data dependency.

5.2 *Effect of Parallelism*

One of the goals of this work is to introduce scalability in the hardware with regards to serial and parallel operation as per the requirement of different applications. Especially, in deep convolutional neural networks, convolutional layers dominate the computation overhead which directly affects the latency and throughput of the hardware. Hence, it is imperative to find the sweet spot for efficient parallelism existing within the convolutional layers. Among all the parallelism mechanisms studied in [33], output channel tiling provides the best throughput in FPGA fabric which performs convolution across multiple output channels for a given input channel, simultaneously. As a result, we also design the parallelism based on output channel tiling in our hardware. The outcome of the parallelism approach is illustrated in Fig. 5, in terms of the energy efficiency of our hardware accelerator under different data width precision. Our RTL (Register Transistor Level) design can achieve an energy efficiency up to 12.7 GOPS/W when implemented for 8 PEs. Similarly, the performance threshold for 2 and 4 PEs go up to 5.7 and 7.3 GOPS/W, respectively.

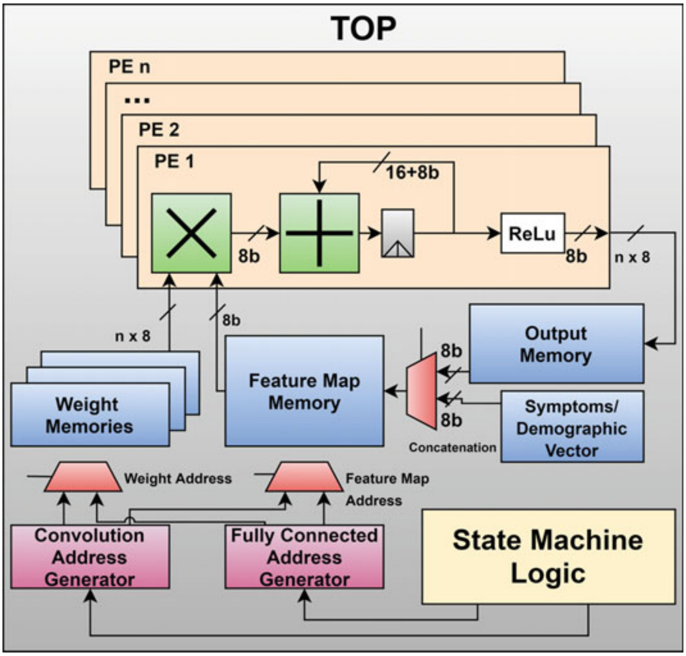

Fig. 4 RespiratorNet hardware architecture designed for the case studies that includes feature map memory and weight memory addressed by the convolution and fully connected modules to fetch data into the Processing Engine (PE) array. The PE array conducts MAC operations and temporarily saves data to the output memory. The control logic of the top defines the functionality of the convolution and fully connected modules. The symptoms vector are only used in Case Study 3 where demographic information and audio samples are supplied to the model. This data is concatenated to the feature map memory to process the finishing fully connected layers of the model. In the top module, finite-state machine manages the concatenation logic

5.3 Quantization: Fixed Point Precision Analysis

All the case studies explored in this work use the quantization level of 8 bits. Going below this level does not provide an appropriate trade-off in terms of hardware performance and model accuracy which is clearly visible from Fig. 6. In the software side, the quantization is applied on kernel weights, bias, and activations for all the convolution layers and fully-connected layers, other than the first layer and the last layer. According to Fig. 6, our model shows acceptable performance while shrinking the model size even to 1/8 of the original 32-bit model. Thus, our proposed hardware architecture has been implemented using a data width of 8-bit fixed-point precision for all four case studies. Even though the change of the data width does not amount to any variation in functional behavior, it affects the operating frequency and power consumption which in turn alters the energy consumption of the hardware. So, it is pivotal to figure out an operating frequency that is consistent with different data width precisions to properly analyze the effect of changing bits over the on-chip

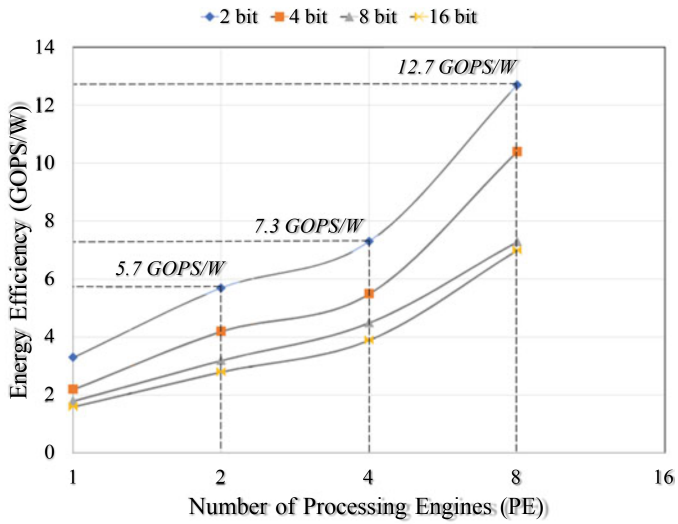

Fig. 5 A scatter plot illustrating the performance against different PE configurations and bit precisions for our proposed hardware. Depending on the input and process flow our hardware is scalable up to 12.7 GOPS/W for 8 PEs in terms of FPGA implementation at 80 MHz clock frequency

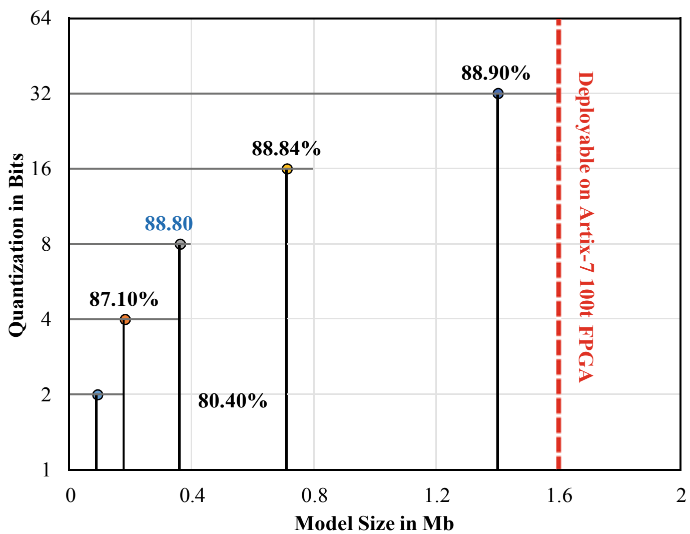

Fig. 6 The effect of quantization on the cough detection architecture is illustrated here. The red line indicates the deployment capacity (1.6 Mb) of the Artix-7 FPGA. Our 8-bit quantized model provides the best trade-off in terms of model size and detection accuracy

energy consumption. In this case, our hardware framework runs at a frequency of 80 MHz to investigate the variation in energy consumption ranging from 16-bit down to 8-bit fixed-point precision as shown in Fig. 7a. As evident in the plot, an 8-bit

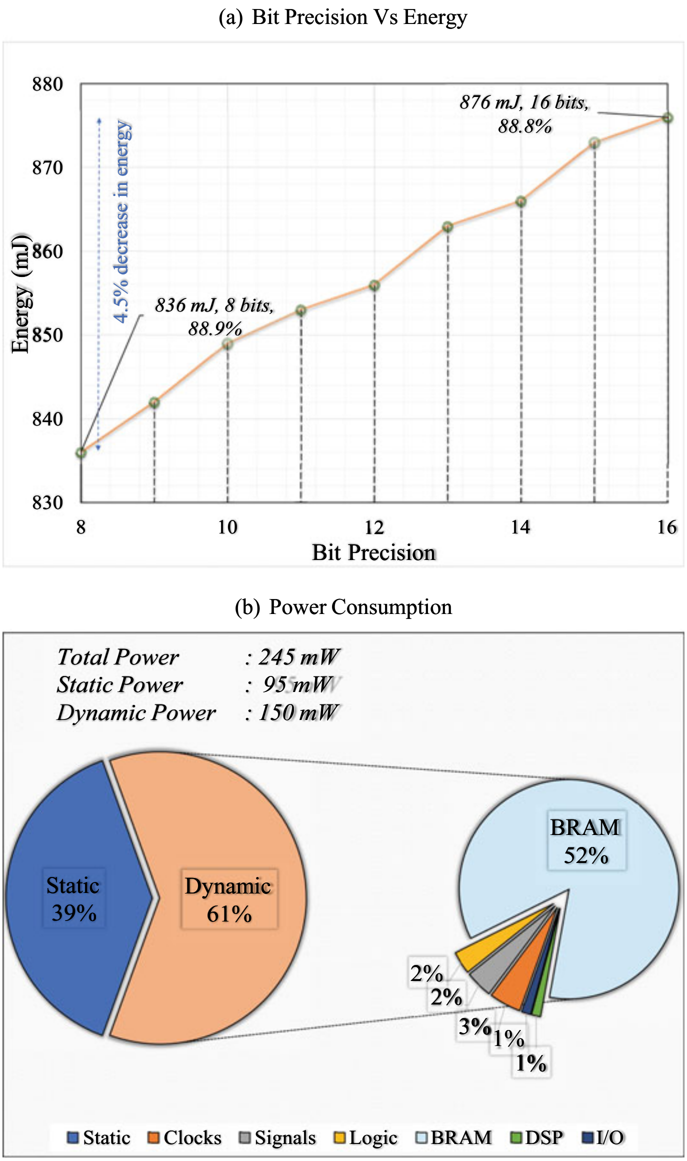

Fig. 7 **a** Illustration of the trend for FPGA energy consumption against different fixed point precision on the respiratory sounds dataset network and **b** breakdown for power consumption in the proposed hardware for a setting of 8 PEs running at 80 MHz

implementation over its 16-bit counterpart results in an energy saving of 4.5% without much deviation in the model classification accuracy for the respiratory sounds dataset network. The proposed hardware utilizes 8 PEs to implement all the different model configurations explored in this work. With a configuration setting of 8 PEs and 8-bit fixed-point precision, most of the on-chip dynamic power is dedicated to BRAMs with only a fraction of the total dynamic power being utilized in clocks, signals, logic, and other areas as highlighted in Fig. 7b. Also, per our analysis, as the number of processing engines increases, the power consumption of the BRAMs and DSPs increases to accommodate the parallel processing of the framework.

6 Hardware Implementation and Results

6.1 FPGA Implementation

On the Artix-7 100t FPGA (Field Programmable Gate Array), the previously mentioned software frameworks are implemented at a clock frequency of 80 MHz. The design of the RTL (Register Transistor Level) is defined in Verilog HDL and synthesized using the Xilinx Vivado 2018.2 tool for the FPGA portion. The option for the Artix-7 100t FPGA comes from the fact that the applications are targeted for embedded implementation of low power, making this component ideal for our objective, with only 135 BRAMs as onchip memory. The results tabulated in the 2 table represent the output of the hardware in this work for the various case studies. In terms of computation, the model with the highest overhead is the one that detects diseases from respiratory sound analysis. The energy consumption of 836 mJ is considerable in this case, with 6 billion operations. Depending on the calculations and size of the model, our RTL design has different results, with energy efficiency varying from 4.1 GOPS/W to 7.3 GOPS/W.

The Table 2 compares various recent hardware designs aimed at CNN acceleration. Ma et al. [34] offers a scalable hardware platform that demonstrates the versatility to deploy CNN architectures in high-level synthesis and optimization. In Huang et al. [35] implementation of a 23 layer, SqueezeNet is introduced. In addition to this on Jafari et al. [10], a low-power multimodal CNN system is accelerated using the same Artix-7 FPGA component used in our work. Our proposed system, when compared, is and 4.3 more energy efficient than the [10, 34] implementations. Although the design is marginally ahead in terms of energy efficiency in Huang et al. [35], with a consumption of less than 33, our work draws significantly low power.

Table 2 Implementation results and comparisons of the proposed case studies with recent CNN hardware designs. The results for our work are obtained for 8-bit fixed point precision at a clock frequency of 80 MHz

Architecture		This	Work		[5]	[10]	[31]
Application	Cough detection (FSDKaggle2018)	Dyspnea detection	Respiratory sounds with demographic info	Cough detection (CoughVID)	Time-series	Image	Image
FPGA platform	Artix-7	Artix-7	Artix-7	Artix-7	Artix-7	Virtex-7	Stratix - V
Input dimension	88,200 × 1	220,500 × 1	220,500 × 1	66,150 × 1	60 × 40 × 1	256 × 256 × 3	256 × 256 × 3
Model size (Kb)	357	198	320	359	N/A	N/A	N/A
Computations (GOP)	2.4	0.6	6	1.8	0.05	0.78	1.5
Fixed point precision	8-bit	8-bit	8-bit	8-bit	8–16 bit	8–16 bit	8–16 bit
#PE used	8	8	8	8	8	N/A	N/A
Frequency (MHz)	80	80	80	80	100	110	100
Latency (s)	2.3	0.4	3.41	2	0.015	0.004	0.012
BRAM (Used %)	81 (60%)	81 (60%)	81 (60%)	81 (60%)	35 (30%)	2715 (92%)	1552 (61%)
Total power (mW)	244	240	245	244	175	27,700	19,765
Energy (mJ)	561	96	836	488	0.35	110.8	237.2
Performance (GOPS)	1	1.5	1.8	0.9	0.3	213.7	134.4

(continued)

Table 2 (continued)

Architecture		This	Work		[5]	[10]	[31]
Efficiency (GOPS/W)	4.1	6.3	7.3	3.7	1.7	7.7	6.8

Table 3 Deploying the RespiratorNet model to commercial off-the-shelf devices including a dual-core Denver CPU, a quad-core ARM A57 CPU, and a combination of ARM CPU+Pascal GPU from the NVIDIA TX2 board

Configuration	CPU Freq (MHz)	GPU Freq (MHz)	Power (mW)	Latency (s)	Performance (GFLOP/s)	Energy (J)	Energy efficiency (GFLOP/s/W)
Denver CPU	345	–	881	10.0	0.019	8.81	0.021
	2035	–	3170	0.9	0.215	2.85	0.068
ARM A57 CPU	345	–	1168	3.7	0.052	4.32	0.045
	2035	–	4425	0.6	0.322	2.66	0.073
TX2 CPU+GPU	2035	1300.5	9106	0.1	1.935	0.91	0.210

6.2 NVIDIA Jetson TX2 Implementation

The trained TensorFlow model of RespiratorNet was implemented on embedded NVIDIA Jetson TX2 platform for evaluating the energy-latency trade-off. Trading off between the computation complexity and the classification accuracy, trained ML models can be deployed to tiny processors and edge devices (e.g. tiny FPGAs, a cell-phone, tablet). At least two hardware-level characteristics are attributed to all DCNN models: the model size and the number of operations per inference, all of which are upper-bounded by the platform resources to which they are deployed or by the inference deadline. Both the hardware resource constraints and the diagnostic latency should follow the application objectives while bringing all the components of the system together. After setting the batch-size to 1, two mobile CPUs like Denver (dual-core) and ARM-Cortex A57 (quadcore) as well as an embedded CPU+GPU implementation with different frequency settings are deployed on the trained model of RespiratorNet. The TX2 development board has been used to calculate all of the parameters as it provides precise on-board power measurement. Table 3 summarizes the implementation. From the Table 3 it can be seen that Denver CPU with a low frequency setting dissipates the least power and takes 10 s to classify one frame. However, the most energy efficient implementation, ARM CPU+GPU, dissipates approximately 10 more power compared to Denver to classify the same frame in 0.1 s. For both the cases, we provided a 5 s frame of recording to the memory.

7 Conclusion

In this chapter, to identify various respiratory symptoms, we propose RespiratorNet, a scalable multimodal CNN software hardware architecture that can take audio recordings, speech information, and other sensor modalities from patient demographic or symptom information. We evaluate and use four distinct publicly accessible databases as case studies to identify respiratory symptoms as part of our experiment. The hardware prototype for RespiratorNet is also scalable and flexible to accommodate different input modalities, data width bit precisions and parallel processing engine numbers. The proposed implementation of hardware has a low power consumption of o 245 mW and achieves an energy efficiency of 7.3 GOPS/W that is 4.3 *times* higher than the implementations of state-of-the-art accelerators. Furthermore the RespiratorNet TensorFlow model is implemented on the NVIDIA Jetson TX2 SoC (CPU+GPU) to provide scalability in terms of off-the-shelf platform implementations and is compared to TX2 single-core CPU and GPU implementations.

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References

1. Zhao, X., Zhang, B., Li, P., Ma, C., Gu, J., Hou, P., Guo, Z., Wu, H., Bai, Y.: Incidence, clinical characteristics and prognostic factor of patients with COVID-19: a systematic review and meta-analysis. MedRxiv (2020)
2. Lee, P.-I., Hu, Y.-L., Chen, P.-Y., Huang, Y.-C., Hsueh, P.-R.: Are children less susceptible to COVID-19? J. Microbiol. Immunol. Infect. (2020)
3. Cho, S.-H., Lin, H.-C., Ghoshal, A.G., Muttalif, A.R.B.A., Thanaviratananich, S., Bagga, S., Faruqi, R., Sajjan, S., Brnabic, A.J.M., Dehle, F.C., et al.: Respiratory disease in the Asia-Pacific region: cough as a key symptom. In: Allergy & Asthma Proceedings, vol. 37
4. Korpáš, J., Tomori, Z.: Cough and Other Respiratory Reflexes./Kasˇel' a Ine´ Respiracˇne´ Reflexy. Veda (1979)
5. Korpáš, J., Sadlonˇova´, J., Vrabec, M.: Analysis of the cough sound: an overview. Pulmonary Pharmacol. **9**(5–6), 261–268 (1996)
6. Amoh, J., Odame, K.: DeepCough: a deep convolutional neural net-work in a wearable cough detection system. In: 2015 IEEE Biomedical Circuits and Systems Conference (BioCAS). IEEE, pp. 1–4 (2015)
7. Ren, H., et al.: End-to-end scalable and low power multi-modal CNN for respiratory-related symptoms detection. In: 2020 IEEE 33rd International System- on-Chip Conference (SOCC) (SOCC 2020)
8. Mazumder, A.N., Ren, H., Rashid, H.-A., Hosseini, M., Chandrareddy, V., Homayoun, H., Mohsenin, T.: Automatic detection of respiratory symptoms using a low power multi-input CNN processor. IEEE Des. Test **2021**, 1–1 (2021). https://doi.org/10.1109/MDAT.2021.3079318
9. Hosseini, M., Ren, H., Rashid, H., Mazumder, A., Prakash, B., Mohsenin, T.: Neural networks for pulmonary disease diagnosis using auditory and demographic information. In: epiDAMIK 2020: 3rd epiDAMIK ACM SIGKDD International Workshop on Epidemiology meets Data Mining and Knowledge Discovery. ACM, pp. 1–5, in press
10. Jafari, A., et al.: SensorNet: a scalable and low-power deep convolutional neural network for multimodal data classification. IEEE Trans. Circ. Syst. I Reg. Papers **66**(1), 274–287 (2019). https://doi.org/10.1109/TCSI.2018.2848647
11. Rashid, H.-A., Manjunath, N.K., Paneliya, H., Hosseini, M., Mohsenin, T.: A low-power LSTM processor for multi-channel brain EEG artifact detection. In: 2020 21th International Symposium on Quality Electronic Design (ISQED). IEEE (2020)

12. Shea, C., Page, A., Mohsenin, T.: SCALENet: a scalable low power accelerator for real-time embedded deep neural networks. In: ACM Proceedings of the 28th Edition of the Great Lakes Symposium on VLSI (GLSVLSI). ACM (2018)
13. Abdel-Hamid, O., Mohamed, A.-R., Jiang, H., Deng, L., Penn, G., Yu, D.: Convolutional neural networks for speech recognition. IEEE/ACM Trans. Audio Speech Lang. Process. **22**(10), 1533–1545 (2014)
14. Piczak, K.J.: Environmental sound classification with convolutional neural networks. In: 2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP). IEEE, pp. 1–6 (2015)
15. Amoh, J., Odame, K.: Deep neural networks for identifying cough sounds. IEEE Trans. Biomed. Circ. Syst. 10(5), 1003–1011 (2016)
16. Nakano, H., Furukawa, T., Tanigawa, T.: Tracheal sound analysis using a deep neural network to detect sleep apnea. J. Clin. Sleep Med. **15**(8), 1125–1133 (2019)
17. Ryu, H., Park, J., Shin, H.: Classification of heart sound recordings using convolution neural network. In: 2016 Computing in Cardiology Conference (CinC). IEEE, pp. 1153–1156 (2016)
18. Aykanat, M., Kurt, O.K.B., Saryal, S.: Classification of lung sounds using convolutional neural networks. EURASIP J. Image Video Process. **1**, 65 (2017)
19. Perna, D., Tagarelli, A.: Deep auscultation: predicting respiratory anomalies and diseases via recurrent neural networks. In: 2019 IEEE 32nd International Symposium on Computer-Based Medical Systems (CBMS). IEEE, pp. 50–55 (2019)
20. Rocha, B.M., Filos, D., Mendes, L., Vogiatzis, I., Perantoni, E., Kaimakamis, E., Natsiavas, P., Oliveira, A., Ja´come, C., Marques, A., et al.: A respiratory sound database for the development of automated classification. In: International Conference on Biomedical and Health Informatics. Springer, pp. 33–37 (2017)
21. Liu, R., Cai, S., Zhang, K., Hu, N.: Detection of adventitious respiratory sounds based on convolutional neural network. In: 2019 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS). IEEE, pp. 298–303 (2019)
22. Perna, D.: Convolutional neural networks learning from respiratory data. In: 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). IEEE, pp. 2109–2113 (2018)
23. Pham, L., McLoughlin, I., Phan, H., Tran, M., Nguyen, T., Palaniappan, R.: Robust Deep Learning Framework For Predicting Respiratory Anomalies and Diseases (2020). arXiv:2002.03894
24. Demir, F., Sengur, A., Bajaj, V.: Convolutional neural networks based efficient approach for classification of lung diseases. Health Inf. Sci. Syst. **8**(1), 4 (2020)
25. Acharya, J., Basu, A.: Deep neural network for respiratory sound classification in wearable devices enabled by patient specific model tuning. IEEE Trans. Biomed. Circ. Syst. **14**(3), 535–544 (2020)
26. Laguarta, J., Hueto, F., Subirana, B.: COVID-19 artificial intelligence diagnosis using only cough recordings. IEEE Open J. Eng. Med. Biol. (2020)
27. Fonseca, E., Plakal, M., Font, F., Ellis, D.P.W., Favory, X., Pons, J., Serra, X.: General-purpose tagging of freesound au- dio with audioset labels: Task description, dataset, and baseline (2018). arXiv:1807.09902
28. Piczak, K.J.: ESC: Dataset for environmental sound classification. In: Proceedings of the 23rd ACM international conference on Multimedia, pp. 1015–1018 (2015)
29. Orlandic, L., Teijeiro, T., Atienza, D.: The COUGHVID crowd- sourcing dataset: A corpus for the study of large-scale cough analysis algorithms (2020). arXiv:2009.11644
30. Abadi, M. et al.: TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems (2015). http://www.tensorflow.org/
31. McFee, B., Raffel, C., Liang, D., Ellis, D.P.W., Matt McVicar, Battenberg, E., Nieto, O.: librosa: Audio and Music Signal Analysis in Python (2015)
32. Rocha, B.M., Filos, D., Mendes, L., Serbes, G., Ulukaya, S., Kahya, Y.P., Jakovljevic, N., Turukalo, T.L., Vogiatzis, I.M., Perantoni, E., et al.: An open access database for the evaluation of respiratory sound classification algorithms. Physiol. Measur. **40**(3), 035001 (2019)

33. Zhang, C., Li, P., Sun, G., Guan, Y., Xiao, B., Cong, J.: Optimizing FPGA-based accelerator design for deep convolutional neural net- works. In: Proceedings of the 2015 ACM/SIGDA international symposium on field- programmable gate arrays, pp. 161–170 (2015)
34. Ma, Y., Suda, N., Cao, Y., Seo, J., Vrudhula, S.: Scalable and modularized RTL compilation of convolutional neural networks onto FPGA. In : 2016 26th International Conference on Field Programmable Logic and Applications (FPL). IEEE, pp. 1–8 (2016)
35. Huang, C., Ni, S., Chen, G.: A layer-based structured design of CNN on FPGA. In: 2017 IEEE 12th International Conference on ASIC (ASICON). IEEE, 1037–1040 (2017)

A Comprehensive Telemedicine Service in Hong Kong Provided Through a Mobile Application

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Abstract On January 23, 2020, the index case of COVID-19 was diagnosed in Hong Kong. Since then, the number of cases has risen at an alarming rate. In anticipation of an outbreak, the Hospital Authority in Hong Kong actively reduced the number of clinic sessions in February 2020 to reduce clinic attendance and hospital admissions and thus reduce the risk of cross-infection among patients. The Hospital Authority is the official government body responsible for public healthcare in Hong Kong. Every year, approximately 13.5 million patients attend outpatient clinics across seven clusters in the Hospital Authority. However, COVID-19 has severely disrupted

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public healthcare services, leading to accumulating clinical caseloads and substantial delays in diagnosis and treatment. The United Christian Hospital and Tseung Kwan O Hospital, which were pioneers of the Hospital Authority Smart Hospital Project, were the first hospitals in Hong Kong to pilot the use of telemedicine during COVID-19 to mitigate service disruptions. While the Zoom videoconferencing platform was adopted as the official app for telemedicine in the early phase of implementation, there were concerns about the potential vulnerability of patients' privacy when using this platform. A series of security assessments of the Zoom client was performed to ensure that patients' data were encrypted and vulnerabilities were resolved. The Zoom client was subsequently incorporated into HA Go, the official patient mobile app of the Hospital Authority. Patients can attend teleconsultations through this app, which enables a comprehensive range of functions, including making future appointments, viewing prescription and medication-dispensing records, delivering educational videos, sending medication collection reminders to patients as push notifications and making payments. The system allows patients to bring their prescriptions to regional pharmacies to obtain their medications and thus avoid traveling long distances to the hospital, which may expose them to the coronavirus. This chapter highlights the experience of developing a telemedicine program for public healthcare services in Hong Kong.

Keywords Head and neck · Otolaryngology · Hong Kong · COVID-19 · Cancer

1 Introduction

The 2019 novel coronavirus disease (COVID-19) pandemic has affected over 182 million people worldwide [1] and has severely disrupted healthcare systems in various countries since its onset. Being the most densely populated city in southern China, the Hong Kong Special Administrative Region (HK) faced the first confirmed COVID-19 case on January 23, 2020. The first case was imported from mainland China, but evidence of community spread through local transmission followed on February 2, 2020. The number of cases in Hong Kong rapidly increased in March 2020, with a large proportion of cases being imported from Western countries [2].

In Hong Kong, healthcare is delivered via a dual-track system. The public healthcare sector, which is under the administration of the Hospital Authority, is responsible for 90% of inpatient services, whereas the private healthcare sector is responsible for the remaining 10%. The Hospital Authority is a statutory government body established in 1990 in Hong Kong [3]. It is responsible for managing public hospital services and formulating health policies for over 7.55 million people in Hong Kong. In 2019, there were 2.16 million accident and emergency department attendances, 7.9 million specialist outpatient clinic attendances and 6.37 million primary care clinic attendances in the seven Hospital Authority regions in Hong Kong, which are known as "clusters" [4]. During the COVID-19 pandemic, in anticipation of a potentially rapid increase in the number of confirmed cases and given the limited resources in the public healthcare system, there was tremendous pressure to reduce the number of hospital admissions and clinic attendances in early February 2020 [5].

2 Smart Hospital Initiatives

Hospitals under the Kowloon East Cluster of the Hospital Authority were the pilot sites for the "Smart Hospital Initiatives". Through proactive application of information technology and the development of smart hospital projects, the Hospital Authority aimed to improve the quality of healthcare services. The Smart Hospital Initiatives involved the development of smart wards, smart clinics and smart operation theatres, which collectively aimed to enhance the efficiency of healthcare services, reduce costs and provide greater convenience to patients and their families [6].

3 Utilization of Telecare to Mitigate Service Disruption

To reduce the number of clinic attendances while avoiding delays in diagnosis and treatment, the Telecare Task Force was officially launched in the Kowloon East Cluster of the Hospital Authority in February 2020 to explore feasible options for utilizing technological advances to substitute in-person patient visits with telecare. The Telecare Task Force was responsible for analyzing the need for telemedicine in various specialties and supporting the implementation of telemedicine programs. Administrators, team leaders and frontline staff who were willing to initiate telemedicine programs for their teams were invited to join the program. Technical support was provided by the hospital's Information Technology Department. To ensure the sustainability of the telemedicine program, funding was provided at the hospital administration level. The applications and the frequency of use of this type of telemedicine in clinical care were regularly reviewed.

To accomplish these telecare sessions, in the early stages the Zoom videoconferencing platform was adopted by the Hospital Authority as an app that complied with the Health Insurance Portability and Accountability Act [7–9]. This platform was endorsed for telecare by the Central Credentialing Committee of the Hospital Authority of HK. To enable the use of Zoom for telecare, a dedicated hardware setup was required at the clinic (Fig. 1). An encrypted wireless network was set up, and additional mobile devices, such as tablets or laptops with high-resolution webcams, speakers, and microphones, were purchased. The setup was designed to simulate a typical face-to-face consultation where doctors could record the consultation summary using the Clinical Management System (CMS) on a desktop workstation and, at the same time, eye contact between doctors and patients could be maintained. Proper lighting was essential, and thus each camera was set up so that it was not facing a window, as that may have caused extreme backlighting [10, 11].

A dedicated telecare website was launched to introduce this new service to patients, including the workflow for enrollment and instructions on how to install

Fig. 1 Hardware setup during tele-consultation

Zoom and establish a teleconsultation (Fig. 2). Patients were required to read information regarding the potential pitfalls of telecare [12], including potential breaches of their privacy; suboptimal consultation quality due to network and software issues; and the inability to conduct a physical examination, which, if necessary, would require rescheduling the appointment. Patients were also required to sign an online electronic consent form to enroll in this new telecare service. An appointment was then assigned to the patient through SMS and email.

Fig. 2 Telecare website for enrollment and technological support

4 Medicolegal and Safety Concerns

Prior to the launch of the telecare service, a proportion of frontline doctors were reluctant to adopt telecare. Multiple questions were raised during a meeting, including:

- Does it work? Is it safe?
- Will there be any medicolegal consequences for misdiagnosis if a physical examination is not performed?
- Will teleconsultation be covered by medical insurance?
- Is it accepted by the community?

To mitigate these concerns about privacy and potential medicolegal consequences of the use of telemedicine, the Medical Council of Hong Kong published a guideline for telemedicine highlighting doctors' obligations to meet all legal and ethical requirements when practicing telemedicine [13]. Specifically, standards of care that protect patients during face-to-face medical consultations apply equally to telemedicine. The doctor must ensure that a telemedicine interaction is suitable for the patient and that the standard of care delivered via telemedicine is reasonable, considering the specific context. Any advice delivered to the patient by the doctor should be documented in detail. Doctors must ensure that the patient's confidentiality and data integrity are not compromised. Information obtained from the teleconsultation must be secure and encrypted to prevent access by any unauthorized third parties. The patient's identity must be verified before sending sensitive information by electronic means. The contravention of ethical guidelines may render a doctor liable to disciplinary proceedings. The ethical guidelines should not be construed to authorize a doctor to engage in medical practice outside Hong Kong or to regulate doctors from other countries who practice telemedicine on patients in Hong Kong. Medical practitioners who practice telemedicine on patients in Hong Kong must be registered with the Medical Council of Hong Kong. Doctors should adhere to well-established principles and standards guiding privacy, records security, informed consent and safe prescribing. If the quality of a telemedicine consultation is affected by technical or environmental limitations, the consultation must be terminated and alternative means must be considered [13].

The doctor-patient relationship is the cornerstone of providing proper medical care to patients. The establishment of a doctor–patient relationship may not be easy, especially when the doctor and patient are in separate locations and/or have no existing in-person relationship. Thus, it is advisable to practice telemedicine only when a prior in-person relationship exists between a doctor and a patient. Moreover, a doctor–patient relationship is based on trust and mutual respect. It is therefore essential that the doctor and the patient are able to identify each other reliably when telemedicine is used. In case of doubt, the doctor should advise an in-person consultation with the patient [13].

In addition, there were concerns during the early phase of implementation of telecare about the potential vulnerability of Zoom to "Zoombombing", or hijacking, during video conferencing [14] and to privacy breaches. The Hospital Authority in HK underwent a series of security assessments on the updated Zoom client to confirm that data sharing with social media platforms was no longer allowed. The analysis showed that these vulnerabilities were resolved and end-to-end encryption was enforced. To protect patients, the Information Technology and Health Informatics Department of the Hospital Authority recommend that clinicians and patients use the latest version of the Zoom client with a corporate account to enable enterprise security features. Furthermore, it is recommended that a password be set for every meeting and that the meeting details and password be exclusively disclosed to participants. Finally, recommendations suggest enabling the "lock" function once all participants have joined the meeting to avoid intrusion.

To ensure that the correct patient is seen at the right time using Zoom teleconsultation, the appointment date and time, Zoom conference ID and password are sent to the patient by email and SMS. Two-way ID verification is then adopted. Patients are asked their date of birth or the last three digits of their HK identity card number and they are asked to show their unique outpatient appointment slip to the web camera [15]. Doctors and nurses engaging in a teleconsultation session also need to be clearly identified by their full names and titles [8]. After each consultation, a new appointment slip and prescription sheet are simultaneously mailed and sent to the patient by e-mail. Patients may then visit the pharmacy at a dedicated hospital within 7 days to obtain the prescribed medications, with payment made on site at the pharmacy [15].

5 Streamlining Telecare Using a One-Stop Mobile App "HA Go"

A well-planned and structured program is essential for the large-scale implementation of telemedicine across Hong Kong. The Information Technology and Health Informatics Department of the Hospital Authority, therefore, developed an official app called "HA Go" for all patients in the Hospital Authority. HA Go is a one-stop mobile application that aims to enhance patients' experiences and improve health outcomes. HA Go allows patients to submit an application for an appointment at a specialist outpatient clinic and review upcoming appointments, past attendance records and clinical records, such as drug dispensing and allergy records and dispensed drug information. Moreover, healthcare professionals can prescribe educational materials and exercises for patients to access via HA Go. All the information is documented and encrypted in the HA Go app. In addition, HA Go facilitates online payment of consultation fees and drug charges using various methods, namely credit cards, bank transfers, Apple Pay, Google Pay, Alipay and WeChat Pay (Fig. 3). It also supports teleconsultation via embedded Zoom and thus provides a one-stop service to patients, such that they do not need to install a separate app. Appointment reminders are sent automatically to the patient's HA Go app. With a few clicks, patients are able to join teleconsultations with their physicians (Fig. 4). As the app requires activation

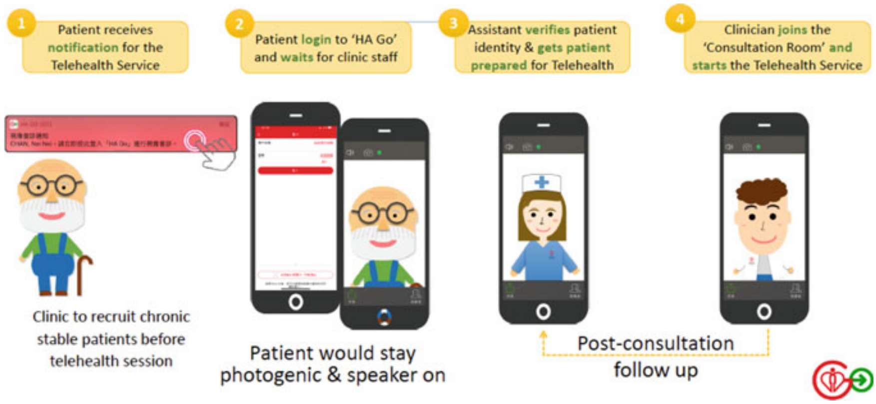

Fig. 3 Patients' perspective in using "HA Go" app for tele-consultation

Fig. 4 Electronic payment for tele-consultation

in person, patients' identities are verified and unique to each account. Each time the app is used, the patient must log in using biometrics (e.g. fingerprint) or a password, which ensures that the right patient is seen, the correct clinical information is discussed and patients' confidentiality is not violated.

During the writing of this book chapter, hospitals in the Kowloon East Cluster were undergoing a trial for home delivery of prescribed medications to obviate the need for patients to go to the hospital pharmacy to obtain their medications. Under this system, the prescription order is sent to the pharmacy and the patient simultaneously through HA Go. Patients receive a QR code on their HA Go app. They can then decide to obtain their medications by visiting the hospital or local pharmacy or have the medications delivered to their home by courier. This precludes patients from queuing in hospital pharmacies and reduces the chance of cross-transmission of the coronavirus. It is of the utmost importance that the correct medications are prescribed and dispensed to the right patients; thus, the courier checks the barcode of each medication against the QR code sent to the patient's HA Go app to confirm the identity of the patient and verify the prescription.

Using the HA Go app, health education materials, such as videos and leaflets, can be delivered to patients. This is particularly useful for home-based exercises. Patients can follow the instructions and demonstrations on the videos to perform their exercises at home during the COVID-19 pandemic. The app also allows physicians or therapists to confirm their patients' compliance with their prescriptions at home or in the community. After each time the prescribed video is played, the time and duration of the video is logged. In addition, this serves as a diary to remind patients to exercise at home. To ensure corporate-wide usage of HA Go and implementation of health education via telemedicine, all educational information has been endorsed by the coordinating committees of different specialties, which comprise the department heads of all seven clusters of the Hospital Authority. Videos and pamphlets were proof-read and approved before they could be uploaded to the platform.

6 Future Work in Patient Empowerment Using "HA Go"

MyHealth module of the HA Go app is currently under development. Soon, patients can record their own health-related parameters, such as body weight, body mass index, body temperature, blood pressure, pulse, blood glucose levels, dizziness score, pain score, peritoneal dialysis information and uterine contraction times. The data can be plotted as a chart locally within the app for self-monitoring and evaluating treatment efficacy (Fig. 5). The data will also be uploaded to the Hospital Authority's cloud server to allow doctors to view the patients' recorded data during consultations on the CMS and adjust medications when necessary. In the foreseeable future, patients will also be able to use Apple Health or Android-compatible Internet of Things health-monitoring devices to measure their heart rate, blood pressure, temperature and blood glucose level. These measurements will be synchronized automatically to the Hospital Authority's cloud server. This will provide an easy and reliable method for documentation and self-monitoring.

During the COVID-19 pandemic, various countries have implemented telemedicine to bring medical care to patients while minimizing the risk of transmission of COVID-19 among patients and clinicians. Clinicians from University of California, San Francisco (UCSF) utilized telemedicine to care for palliative care patients in the ambulatory settings. Apple FaceTime, Facebook Messenger, Google Hangouts and Skype were used [16]. In Italy, telemedicine service was designed for heart failure patients, and the service was based on phone calls. This eliminated the possible social disparities (e.g. accessibility of clinical service was only available to people with available technological device and/or capacities to use the service) [17].

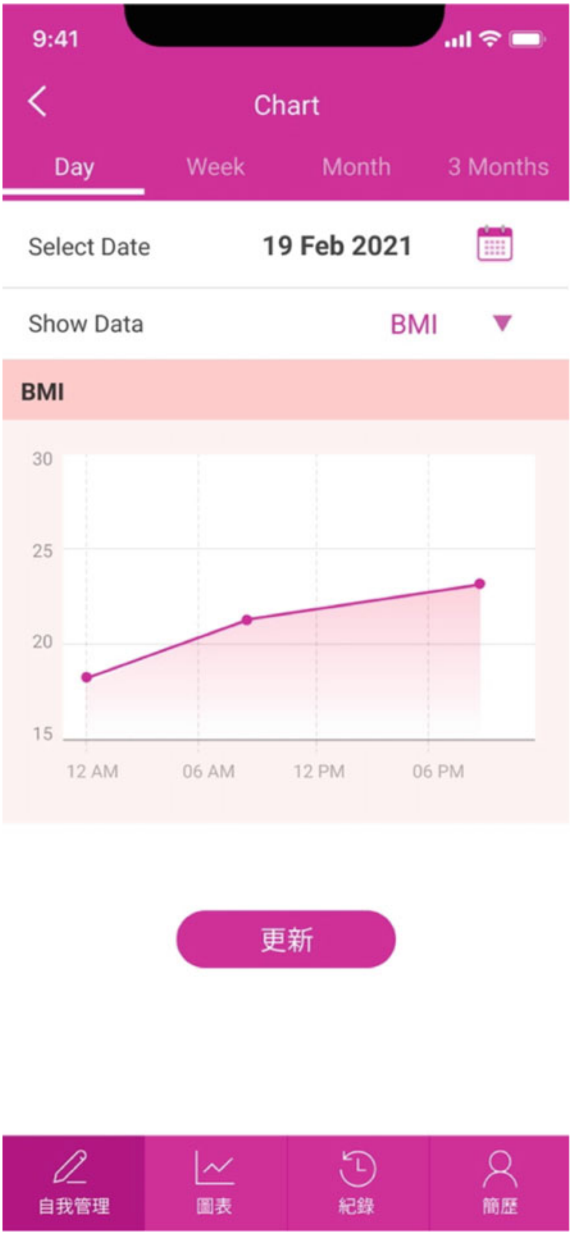

Fig. 5 MyHealth module for patients' self-monitoring of health parameters

In India, telemedicine was limited by the low internet penetration. Only 36% of the overall population had access to internet [18]. In Chennai, southern part of India, teleconsultations were conducted to 2864 patients with diabetes mellitus. Patients were enquired about their symptoms and diabetic control. After the consultation, prescriptions were sent to patients by email [18]. In Western part of China, WeChat was used to offer online consultations. 31,905 patients with chronic diseases received tele-consultation to reduce the number of patient visits in the outpatient clinics and internet-based drug delivery service was provided for this group of patients. 5G Dual Gigabit Network was also utilized in areas where there were a limited number of radiologists. 5G Network was used by radiologists to remotely interpret Computed Tomography (CT) films which were undertaken over 300 km (Range 20–1191 km) away from the central node at the West China Hospital of Sichuan University. Web-based and real time video conference was held to discuss cases of coronavirus disease in rural areas of Western China [19].

In Hong Kong, telemedicine was implemented for patients in the public sector during the COVID-19 panedemic. The HA Go telecare app was designed to provide a one-stop service for patients in Hong Kong. It provides an easy, yet secure, method of teleconsultation. It was designed to be simple for patients and frontline users and to be incorporated into the typical clinical workflow. It includes a wide range of functions, such as delivering educational videos and e-prescriptions, sending medication collection reminders as push notifications, and settling payments. Over the past year in Hong Kong, telemedicine has been adopted in isolation wards to reduce the risk of infection transmission to nurses and physicians. It has also been used successfully in otorhinolaryngology, ophthalmology, psychiatry, clinical psychology, orthopedics and traumatology, family medicine, hepatology, respiratory and pain clinics. Its use was subsequently expanded to nurse clinics, outreach programs, allied health departments catering for outpatient wound care and palliative home care and for seminars on oromyofunctional therapy for obstructive sleep apnea. In the future, the application of telemedicine may extend to providing services to elderly or disabled patients to minimize the hassle and cost of traveling between institutions.

References

1. World Health Organization. Coronavirus disease (COVID-19) Pandemic
2. The Government of Hong Kong Special Administrative Region. Coronavirus Disease (COVID-19) in HK (2020)
3. Food and Health Bureau, The Government of HKSAR. Report of the Steering Committee on Review of Hospital Authority (2015)
4. Hospital Authority. HA Annual Report 2018–2019 (2019)
5. Chan, J.Y.K., Wong, E.W.Y., Lam, W.: Practical aspects of otolaryngologic clinical services during the 2019 novel coronavirus epidemic: an experience in Hong Kong. JAMA Otolaryngol. Head Neck Surg. (2020)
6. Cheng, I.: Development of telehealth services (2021)
7. Perrin, P.B., Pierce, B.S., Elliott, T.R.: COVID-19 and telemedicine: a revolution in healthcare delivery is at hand. Health Sci. Rep. **3**(2), e166 (2020)
8. Bokolo, A.J.: Use of telemedicine and virtual care for remote treatment in response to COVID-19 pandemic. J. Med. Syst. **44**(7), 132 (2020)
9. Loeb, A.E., Rao, S.S., Ficke, J.R., Morris, C.D., Riley, L.H., 3rd., Levin, A.S.: Departmental experience and lessons learned with accelerated introduction of telemedicine during the COVID-19 crisis. J. Am. Acad. Orthop. Surg. **28**(11), e469–e476 (2020)
10. Tanaka, M.J., Oh, L.S., Martin, S.D., Berkson, E.M.: Telemedicine in the era of COVID-19: the virtual orthopaedic examination. J. Bone Joint Surg. Am. **102**(12), e57 (2020)
11. Rifat Latifi, C.R.D., Merrell, R.C.: Telemedicine, telehealth and telepresence—Principles, strategies, applications, and new directions. **1** ed2021
12. Hong, Y.R., Lawrence, J., Williams, D., Jr., Mainous, I.A.: Population-level interest and telehealth capacity of US hospitals in response to COVID-19: cross-sectional analysis of google search and national hospital survey data. JMIR Public Health Surveill. **6**(2), e18961 (2020)
13. The Hong Kong Medical Council. Ethical Guidelines on Practice of Telemedicine (26) (2019)
14. Marczak, B., Scott-Railton, J.: A quick look at the confidentiality of zoom meetings (2020). https://citizenlab.ca/2020/04/move-fast-roll-your-own-crypto-a-quick-look-at-the-confidentiality-of-zoom-meetings/
15. Lee, A.K.F., Cho, R.H.W., Lau, E.H.L., Cheng, H.K., Wong, E.W.Y., Ku, P.K.M., et al.: Mitigation of head and neck cancer service disruption during COVID-19 in Hong Kong through telehealth and multi-institutional collaboration. Head Neck **42**(7), 1454–1459 (2020)
16. Calton, B., Abedini, N., Fratkin, M.: Telemedicine in the time of coronavirus. J. Pain Sympt. Manag. **60**(1), e12–e14 (2020)
17. Salzano, A., D'Assante, R., Stagnaro, F.M., Valente, V., Crisci, G., Giardino, F., et al.: Heart failure management during the COVID-19 outbreak in Italy: a telemedicine experience from a heart failure university tertiary referral centre. Eur. J. Heart Fail. **22**(6), 1048–1050 (2020)
18. Dash, S., Aarthy, R., Mohan, V.: Telemedicine during COVID-19 in India-a new policy and its challenges. J. Public Health Policy **42**(3), 501–509 (2021)
19. Hong, Z., Li, N., Li, D., Li, J., Li, B., Xiong, W., et al.: Telemedicine during the COVID-19 pandemic: experiences from western China. J. Med. Internet Res. **22**(5), e19577 (2020)

Adapting to Live in the Global Pandemic Era: Case Studies

James Jin Kang

Abstract The COVID-19 Pandemic (Pandemic) has had a dramatic impact on societies around the world affecting every aspect of people's lives. In one particular example, it has changed the way work is perceived and attitude towards working lives, such as an increased adoption and greater acceptance of working from home. From the perspective of IT networking, such changes have caused network capacity issues in relation to internet speed and capacity. The changes are so significant that humans have adapted to a new way of living in the realm of businesses, jobs, healthcare, education, trades, politics, economics, families and relationships. This chapter illustrates some applications and solutions that can be used to aid the adaptation processes with case studies of security concerns such as privacy as well as how quickly a new business can be introduced to cope in the era of the pandemic.

Keywords Adaptive methods · Privacy · Security · Authentication · Health data · Patient monitoring · Health data for identification · Internet speed enhancement · Self-driving Vehicle · TikTok privacy threats

1 Introduction

One of the most significant changes experienced after the arrival of the Pandemic was the ways in which people work in order to avoid being close to others (i.e., social distancing). This instantly caused network access issues as internet services providers could not cope with the rapid changes and demand in service location. Whilst corporate or government organizations have fast internet access capacities, most residential users have a best effort plan, which is designed for reasonable use. When entire households simultaneously use the internet for work, entertainment, education or video meetings, internet speed has diminished capacity to serve all of these purposes at once. Internet service providers cannot simply move the corporate

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capacity to home users instantly on demand due to logistical and contract matters despite it being technologically possible.

To track the spread of the virus within the population, The Australian Government initially introduced a location tracking app called 'CovidSafe' along with other countries who developed their own apps that served similar purposes. In some cases, however, these apps led to privacy issues by sharing and uploading personal information along with social media platforms such as TikTok, which has been more prevalent amongst the younger generation (particularly as they were unable to attend school in person). Arguably, the app has been used to access and retrieve personal data by unauthorized parties. Some security concerns arose in relation to the tracking app and some social media apps, which will be discussed in this chapter as case studies. To avoid direct contact with others in public transportation networks, a driverless taxi service was launched in the United States. Passengers sit in the back while the car is driven by a robot. While the service had been planned for some time, it was launched early to meet the demands caused by the Pandemic situation. Finally, health data-based identification [1] is briefly discussed to illustrate how it can be used to identify a user of equipment such as smartphones. Currently it is possible to track the location of the smartphone and even raise alarms [2–4], however there is no way to verify the owner of the phone, which is easily given to others. Using the health data along with IoT network for location tracking system [5], it is feasible to track down the whereabouts of the user who may have contracted coronavirus. This idea could also be used in many other areas such as proving alibis in legal cases, authentication of devices, firearm authentication via health data and biometrics to improve security.

This chapter will explore the various applications that were either developed during the Pandemic or were otherwise used with more frequency to assist people to adapt to the new ways of living, in addition to analyzing some issues that arose.

Security issues of real-time tracking and observation of potential infectious people to verify self-quarantine

It is crucial from an epidemiological and public health perspective to be able to rapidly identify and monitor patients who are infected as seen in the COVID-19 pandemic. Mobile health technologies can provide information on individuals who may be unwitting carriers or who may have been exposed to an outbreak. In certain cases, technology can flag those who may meet criteria to be considered for quarantine. Political issues such as forcing suspected virus carriers to an isolated location for quarantine can be eased by mobile Health (mHealth) technology which can track and provide real-time monitoring of potential patients.

Governments or agencies can have better visibility of population metrics, use modelling to predict likely distributions of pathogens and develop control and management capabilities in a manner which is transparent to the public—avoiding the risk of generating panic.

Educating the public will be key to preparing for future virus outbreaks, in the future it will be feasible to pinpoint geographic areas and regions to prioritize monitoring targets using algorithms.

With the advent of any technological developments, there will be both positives and negatives. It will be essential to consider issues relating to security, in particular, being aware of the risk of privacy breaches given the highly sensitive nature of such incidents.

There have been various tracking apps across countries that have been used along with other vaccination tracking apps to track down locations of users who have been exposed or infected. Several issues relating to these have arose, using the Australian Government's CovidSafe app as an example.

The tracking app collects anonymous IDs from other people who are also using the app that users come into short distance range with by coupling each other's phones over Bluetooth. If an individual tests positive to COVID-19, they can share the logged period of time, e.g. last 21 days' worth of contacts stored on the app, and the data will be sent to a server. Health officials can then use this information to trace and inform possible contacts that they may have been exposed to the virus, depending on how close that contact may have been e.g. within a radius of 1.5 m for 15 min. This involves a transfer of data when users exchange anonymous ID with other people using Bluetooth, as well as when the data is transmitted to government servers.

There are several areas in which vulnerabilities can exist:

- Data can be intercepted between a phone and the national data store.
- Bluetooth is required to be kept on all the time, which gives a chance for eavesdropping. The tracking app is not the only app which uses Bluetooth, and other apps may have access to it. It increases the risk of security as those apps may have access to personal information.

1.1 What are Some Issues With Apple iPhones?

The iPhone operating system (iOS) depending on the version, will not allow background running of the app, which needs to always be on and active to work. This can drain the phone battery and cause some people to be reluctant to install the app.

If the iOS version allows for background app functionality using features such as Background App Refresh [6], it should be checked that it works for the tracking app. The Australian Government has released the source code of the app in order to maintain transparency. A report [7] says that tracking app running in the background had a minimal impact on the battery life, although it did not disclose the specifications such as the phone model or OS version such as Android or iOS which they tested it with.

1.2 Vulnerabilities to Data Interception

Data that is sent to national storage includes your name, mobile phone number, age range and postcode. Regardless of this, the transmission could include sensitive information such as possible confirmation of the virus. Knowing that a person associated with a certain mobile phone number could be diagnosed with COVID-19 can lead to privacy issues. The phone number itself causes 'privacy' issues and can be used to verify a target by an attacker. Multi-Factor Authentication (MFA) systems such as the ones used in online banking requires authentication with a code sent to a phone number, and there is potential for an attacker to clone a phone. When pairing up with Bluetooth, users are potentially opening a door to others who may gain access to their phones in public places such as shopping centres, public transport, restaurants and so on.

1.3 Bluetooth Needs to Be Always on, So Users Should Check Bluetooth Status of Other Apps

Many apps require Bluetooth connection to track your location. Apps can log locations users have visited or passed through and may transfer the information to their servers for marketing purposes. By installing the tracking app, users are opening a door for all apps which have Bluetooth permissions. The only way to manage this is to check the app permissions individually. Alternatively, users may have a second phone installed with the tracking app only, though this would not be practical. Some app developers might have ulterior motives to track the location of users, which might not need users to have the app open at the time nor ask for consent. As a solution, users could deny Bluetooth permission for all apps from the start, and grant permissions manually in the settings (e.g., Settings > Privacy > Bluetooth for iPhone) one by one for essential apps only.

1.4 Where Data is Sent to and Stored?

Location and uploaded data are likely to be stored on a centralized cloud-based server in addition to a secondary storage location to house close contact information. It offers an opportunity for attackers to target a single point to attack, like putting all eggs in one basket. Distributing data across multiple locations helps to prevent the risk, however, it increases maintenance and management requirements. Granting access to state governments may be useful for the states to be able to see statistical data, though it causes further vulnerability risks by giving access to more users. It could be more appropriate or easier to process the data centrally and provide information to state governments as needed as an alternative.

1.5 Use of Apps for Patient Monitoring in Disease Outbreaks

A tracking app can be used to identify the previous and current location of the user for diseases or self-quarantine purposes. Mobile health technologies have the potential to identify individuals who may have been exposed to a disease, flagging those who may meet criteria to be considered for quarantine. Governments or agencies can use this data to more comprehensively inform population metrics, develop modelling and to intelligently implement a public health response that can be objective and transparent to the public—avoiding the risk of generating panic. Educating the public will be key in public health responses to future disease outbreaks, and mHealth technologies with algorithms could allow for a localization of public health response to specific geographical areas of need. However, it has potential for privacy issues as well as the efficiency and validity of data depending on how the user can comply with the consent and policy such as terms of use.

2 Privacy Issues on Social Media Platform Tiktok in Pandemic Era

TikTok has been chosen in particular as it caused controversial concerns from media by its privacy breaches accessing and retrieving personal information [8]. In the age of isolation, with friends and family craving social contact, TikTok has emerged as a bonding force. From dance videos to hints and tips for fitness and exercise; TikTok videos are created, uploaded, and viewed across the world. But what is TikTok; who is using it; why is it so controversial; and, why is the Australian government concerned with the app so closely?

2.1 What is TikTok?

TikTok has been around since 2016 and was relatively unknown outside of China where it was developed by the Beijing based company ByteDance. It became a global sensation after its release in global app stores in 2017 with a reported 2 billion downloads globally. The Australian market is significant with an estimated 1.6 million regular users. While the users are typically considered to be in the 16–24 age range, there is substantial use within older generations.

TikTok is a simple concept, users generate short video sequences that are shared through the app. This simplicity is reinforced by their own mission statement [9]:

> TikTok is the leading destination for short-form mobile video. Our mission is to inspire creativity and bring joy.

Lockdowns implemented in response to the Pandemic allowed TikTok to rise in global popularity as forced quarantine isolated social groups. Sharing TikTok experiences allowed friends and family to reconnect with celebrities and politicians joining in. Social media is an important tool in keeping families and friends connected, but often has a negative side. Recent examples have included zoom-bombing and an increase of concerning online behaviors.

2.2 What Information Can Be Collected and How are They Transferred?

According to a lawsuit [10] filed in the USA, TikTok is allegedly gathering users' phone numbers, emails, location, IP addresses, and social network contacts. Concerns have been raised that companies purportedly conceals the transfer of user data, and continues to harvest user and biometric data even after the app is closed. For example, when a user shoots a video and clicks 'next', the video is automatically transferred to servers in China without the knowledge of the user. Even if the user does not save or publish the video, the app transfers the data regardless.

2.3 The Dark Side of TikTok

Like all apps, TikTok is a data gathering service hiding behind a social media facade. Its parent company, ByteDance, has been accused of secretly taking user content and information without consent and transferring data to servers located in China. It has also been accused of concealing the transfer of this data and continuing to record information even when the user would not intend. For example, when a user records a video but does not save or publish the video, it is still transferred to the servers without the user's knowledge.

2.4 What Features and Information Can Be Accessed by TikTok?

TikTok requests a number of permissions on a device during installation, and with the permissions given, it has full access to the camera, microphone, the device's WiFi connection, and the contacts list. This allows the app to do the following:

- take pictures and videos, record audio and sound
- keep the device turned on and start automatically when starting up the phone
- collect GPS and location data along with detailed information of other apps which are running

- read and write to the storage, install and remove shortcuts, and request installation packages.

One critical feature is that the app can access other apps which are running at the same time, such as banking apps. This can give permission to access the data of banking apps for example.

2.5 Where is the Data Stored?

It is widely suspected that data from TikTok may ultimately end up in China. While the company is headquartered in Beijing, a recent quote from the Australian general manager (Lee Hunter) indicated that the data for Australian users is actually stored in Singapore [11] and stated that:

> TikTok does not share information of our users in Australia with any foreign government, including the Chinese government, and would not do so if asked. We place the highest importance on user privacy and integrity.

A bigger challenge is perhaps that of defining data. While the details of users and their videos may be stored in Singapore, there is potential for data to be extracted from the video content. Perhaps generating biometric data to identify people using facial recognition, or mapping rooms using feature extraction from videos generated by users in senior positions. Fake videos could even be generated using deepfake technology. While this may seem far-fetched, there have already been pre-emptive bans within certain organizations to ensure sensitive information is not leaked through shared videos on TikTok. Examples of bans include in Defence forces such as Australia's ADF [12] and the US Department of Defence [13], and even entire countries with the Indian government [14] announcing a ban across its nation.

2.6 ByteDance and Its TikTok Server Location

ByteDance claims that its data are stored in servers in the United States and Singapore, however it is unclear where they store what data.

"We store all TikTok US user data in the United States, with backup redundancy in Singapore," the company said. "Our data centres are located entirely outside of China, and none of our data is subject to Chinese law" [15]. ByteDance operates a separate service called Douyin to serve the Chinese market. ByteDance is based in Beijing, and TikTok says that no data is stored in China. The company announced that they would build a data centre in India, however it is uncertain as India banned TikTok along with other Chinese apps in India allegedly citing reasons to "national security and defence of India, which ultimately impinges upon the sovereignty and integrity of India" [14].

2.7 What Privacy Issues Does TikTok Potentially Have?

TikTok's privacy policy is ambiguous and as of October 2019 states that "You should understand that no data storage system or transmission of data over the Internet or any other public network can be guaranteed to be 100 percent secure". From the user's privacy perspective, TikTok has access to device location and personal information such as contact details. Whilst their servers appear to be located outside of China, it is impossible to confirm nor deny where this data could end up and what the data could be used for. If a user decides to delete their content from their device or if there is a ban, data cannot be retrospectively erased and any information that has already been transferred would be impossible for users to retract.

2.8 Can the Australian Government Actually Ban TikTok?

Enforcing a ban on TikTok is not as easy as it sounds. While the Australian government could request for the removal of the app from App Stores (Apple App Store, Google Play Store), they could only do this for Australian regions and marketplaces. Users would still be able to simply download from another geographical store or a third-party source, and this would also not remove the app from users who already had it installed on their devices. Blocking access to TikTok servers could be implemented in partnership with Internet Service Providers, but, just as with other attempts to block access to services, users can use proxies or VPNs to circumvent these controls. Even in the event of a ban, the vast amount of data already collected on Australian citizens would still be stored and potentially accessible to Chinese authorities for the foreseeable future.

3 Health Data for Identification and Authentication

Biometrics such as voice recognition, retina or fingerprints have been used in various applications for authentication purposes. This however cannot be used in remote applications as the verifications physically require to be close to the sensors. As privacy, which can be improved by protecting personal information using algorithms [16] is a key requirement in eHealth and IoHT technologies, health data can be used for user identification purposes. Whilst one type of health data such as heart rate may provide no identifying information, it could in combination with others represent a unique pattern that is specific to an individual, especially as a trend over time using machine learning. The major expected outcomes for such an application could include (1) assessment of health data traits with measurable and standardized accuracy, (2) building a model of structured attributes that can affect the effectiveness of the health data being used for identification.

Health data can also be used to provide whereabouts of individuals with verified time and location. For example, providing a reliable alibi (proof of absence) is a crucial factor to prove one's innocence. Verifying a person's true identity and location has always been an issue, but now it can be done by personal health devices, which provides identification of individuals via health data of the user along with trusted real-time–space technology. Proving the whereabouts of a person is not always reliable as they rely on witnesses' own descriptions, which is weakened as humans are forgetful and can easily be affected by factors such as fatigue, alcohol or drugs. Using wireless body area network and internet of health things (IoHT) technology, it is possible to identify a person using health data of the user [16–19]. It is also able to provide tracking of location on a time basis using a trusted-time–space server [20], which provides exact locations at a certain time. Whilst a smartphone can prove the location of the device, it cannot prove the true owner of the device is on the location as the phone can be moved to others. Using the health data for identification, it is now possible to prove the owner is holding the device. In addition to biometrics, health data can also be used for authentication to enhance the accuracy. Passwords can be stolen. Even some biometrics such as fingerprints may be stolen. However, it is impossible to steal real-time physiological health data unless the user has been kidnapped. In this sense, authentication of using health data combined with biometrics can enhance the security and authentication.

4 Conclusion

The Pandemic has showcased the resilience and adaptability of human societies. People have rapidly adjusted their lifestyles and have evolved with innovative ideas and changes to make their lives more endurable. This chapter illustrated some applications that gained momentum during the Pandemic such as TikTok and autonomous vehicles, and some issues that arose during the course of this period. However, there is no doubt that those issues can be ironed out and optimized over the course of time. The crisis caused by the Pandemic will be soon over with the rollout of the vaccine currently being deployed across the globe. It is clear that if future pandemics emerge (which have already been predicted), humans will continue to adapt as they have done in the era of COVID-19.

References

1. Kang, J.J.: A military mobile network design: mHealth, IoT and low power wide area networks. In: 2020 30th International Telecommunication Networks and Applications Conference (ITNAC), pp. 1–3 (2020)
2. Kang, J.J., Luan, T.H., Larkin, H.: Alarm notification of body sensors utilising activity recognition and smart device application. In: Proceedings of the 14th International Conference on Advances in Mobile Computing and Multi Media, pp. 105–109 (2016)

3. Kang, J., Larkin, H.: Application of an emergency alarm system for physiological sensors utilizing smart devices. Technologies **5**(2), 26 (2017)
4. Kang, J.J., Luan, T.H., Larkin, H.: Data processing of physiological sensor data and alarm determination utilising activity recognition. Int. J.Inf. Commun. Technol. Appl. **2**(1), 108–131 (2016)
5. Kang, J.J., Khodasevych, I., Adibi, S.: A disaster recovery system for location identification-based low power wide area networks (LPWAN). In: 2017 27th International Telecommunication Networks and Applications Conference (ITNAC), pp. 1–6 (2017)
6. Apple: Updating Your App with Background App Refresh (17 March 2021). https://developer.apple.com/documentation/uikit/app_and_environment/scenes/preparing_your_ui_to_run_in_the_background/updating_your_app_with_background_app_refresh
7. Halliday, F.: COVIDSafe explained: everything you need to know about the Australian government's coronavirus app. PC World. https://www.pcworld.idg.com.au/article/678801/covidsafe-explained-everything-need-know-about-australian-government-coronavirus-app/
8. Kang, J.: China could be using TikTok to spy on Australians, but banning it isn't a simple fix (2020, 20/09/2021). https://theconversation.com/china-could-be-using-tiktok-to-spy-on-australians-but-banning-it-isnt-a-simple-fix-142157
9. TikTok. Our Mission (17 March 2021). https://www.tiktok.com/about?lang=en
10. US District Court Northern District of Califonia. Case 5:19-cv-07792-SVK Document 1 Case 5:19-cv-07792-SVK Document 1. https://www.courthousenews.com/wp-content/uploads/2019/12/Tiktok.pdf
11. Waters, C.: TikTok on thin ice as Parliament prepares to pore over app. In: The Sydney Morning Herald, ed. (2020)
12. Bogle, A.: TikTok not approved for use on Australia's Defence devices. In: ABC News, ed. (2020)
13. Vigdor, N.: U.S. Military branches block access to tiktok app amid pentagon warning. In: The New York Times, ed. (2020)
14. Singh, M.: India bans TikTok, dozens of other Chinese apps (2020, 17 March 2021). https://techcrunch.com/2020/06/29/india-bans-tiktok-dozens-of-other-chinese-apps/
15. TikTok: Statement on TikTok's content moderation and data security practices (2019, 19 March 2021). https://newsroom.tiktok.com/en-us/statement-on-tiktoks-content-moderation-and-data-security-practices
16. Kang, J.J., Dibaei, M., Luo, G., Yang, W., Haskell-Dowland, P., Zheng, X.: An energy-efficient and secure data inference framework for internet of health things: a pilot study. Sensors (Basel) **21**(1), Accessed 2021/01. https://doi.org/10.3390/s21010312. https://www.mdpi.com/1424-8220/21/1/312
17. Kang, J.J.: Systematic analysis of security implementation for internet of health things in mobile health networks. In: Sikos, L.F., Choo, K.-K.R. (eds.) Data Science in Cybersecurity and Cyberthreat Intelligence, pp. 87–113. Springer International Publishing, Cham (2020)
18. Kang, J.J., Larkin, H.: Intelligent personal health devices converged with internet of things networks. J. Mobile Multimed. **12**(3&4), 197–212 (2017 April 30). https://doi.org/10.26421/JMM12.3-4
19. Kang, J.J., Adibi, S., Larkin, H., Luan, T.: Predictive data mining for converged internet of things: a mobile health perspective. Sydney NSW Australia IEEE Xplore: IEEE, pp. 5–10
20. Kang, J.J., Fahd, K., Venkatraman, S., Trujillo-Rasua, R., Haskell-Dowland, P.: Hybrid Routing for Man-in-the-Middle (MITM) attack detection in IoT networks. In: 2019 29th International Telecommunication Networks and Applications Conference (ITNAC), pp. 1–6 (2019)

Towards QR Code Health Systems Amid COVID-19: Lessons Learnt from Other QR Code Digital Technologies

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Abstract The novel coronavirus disease (COVID-19) continuously crippling healthcare systems globally and disrupting movements of people which led to the temporary closure of schools, colleges, universities, industries, and businesses. To reduce the catastrophic impact of the new variant of COVID-19, governments in collaboration with World Health Organization (WHO) emphasize on vaccination of populations. However, several countries witnessed a rapid increase of new infections and deaths which are linked to relaxation of regulations, fake COVID-19 certificates, resistance to adoption of health digital technologies, overburdened health system, lack of personal protective equipment, social risk behaviors, poor policies and standards for immigrants and lack of standardized and synchronized regional and international health information system that facilitates the regular sharing of COVID-19 data, test results and vaccination certificates. Also, accessing COVID-19 data and patient health history data remains a challenge for many health systems. Therefore, we propose the use of secure regional and international quick response code-based health systems to monitor the migration patterns, validate COVID-19 test results and vaccination certificates to facilitate safe regional and international movement of people during the pandemic.

Keywords Quick response · COVID-19 · Health information systems · Digital technology

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1 Introduction

In December 2019, a new infectious respiratory disease emerged in Wuhan, Hubei province, China and was named by the World Health Organization as coronavirus disease 2019 (COVID-19) [1]. The outbreak of COVID-19 continues to burden health systems, globally, disrupting movements of people exacerbated by the temporary closure of schools, colleges, universities, industries, and businesses. As part of the response to reduce the catastrophic impact of COVID-19 and emerging variants, governments in collaboration with World Health Organization (WHO) implemented infection control and preventive measures such as social distancing, face masking, regular temperature checking, contact tracing, quarantine and self-isolation [2]. This follows enacted stringent COVID-19 restrictions and guidelines such as maintaining social distancing in public spaces, wearing of face masks, recursive national lockdowns, and regular checking of temperature in strategic entry points [3]. More recently, several countries started loosening travelling restrictions to allow the swift reopening of economic activities after the successful development of WHO approved COVID-19 vaccines [4], which subsequently intensified the vaccination of populations [5]. Unfortunately, some countries like India, United Kingdom and South Africa witnessed COVID-19 surge partially linked to relaxation of regulations [6], resistance to adoption and use of health digital technologies, overburdened health systems [7], social unrest, poor sanitation [8], poor adherence to COVID-19 preventive measures, poor vaccines efficacy, insufficient vaccines, fake COVID-19 certificates [9] and dearth of medical equipment such as the testing kits, personal protective equipment, masks, and ventilators [10].

To alleviate these impediments, several digital technologies have been implemented to monitor, trace, track people and enhance the implementation and adherence to COVID-19 infection control and preventive measures. Digital and emerging technologies such as big data, cloud computing, geographical information systems, Internet of Medical Things (IoMT), 5G technology, blockchain [11], artificial intelligence, Internet of Things (IoT) and fog computing have been adopted to develop social distancing applications (apps), contact tracing apps among others to fight against COVID-19 pandemic [12]. However, despite relying on emerging digital technologies, several countries developed varying applications for surveillance, screening, quarantine, and self-isolation which led to varying data formats, data management, security, and privacy. This has led to data synchronization and standardization problems [13] which subsequently affect international and regional sharing of COVID-19 data.

1.1 Contribution of the Study

COVID-19 brought transformative shifts in healthcare service delivery by integrating digital technologies to promote effective sharing of health information, remote monitoring, and virtual care. Among digital technologies, quick response code has been extensively adopted in developing COVID-19 contact tracing applications and vaccination certificates or immunity passports. This has been necessitated to alleviate issues emanating from paper-based vaccination cards. Notably, the authenticity and reliability of COVID-19 test results, immunity passports or vaccination certificates are vulnerable to forgery [14], counterfeits, issued corruptly and they can easily tear [15], get lost and potentially violate individual's privacy [16]. Despite all these challenges, vaccination certificates or immunity passports and negative-COVID-19 test results are slowly becoming mandatory for travelling, therefore, there is a need to synchronize, authenticate, sharing and provide remote access to vaccination information. In such circumstances, the adoption of QR code health systems amid pandemics like COVID-19 is inevitable. Such QR code health systems may be used to validate COVID-19 certificates and accessing COVID-19's patient history remotely as well as vaccination information and subsequently facilitate contact tracing and improve healthcare service delivery. Currently, individual's COVID-19 history data is not easily accessible regionally and internationally as people travel from one place to the other [17]. However, the recent advances in QR code technology in health systems could alleviate such impediments. Therefore, this study proposes the potential integration of quick response code in health information system to monitor the migration patterns, validate COVID-19 certificates and tracking people's COVID-19 health status to facilitate regional and international travel amid the COVID-19 pandemic. The study sought to address the following research objectives:

- Identify QR code-based applications deployed to tackle COVID-19.
- Identify digital technologies that could facilitate the integration of QR technology in health systems.
- Highlight compounding challenges, threats and impediments that could hinder the implementation of the QR code health system.

2 Related Work

2.1 Quick Response Code in Healthcare

Quick response codes are two-dimensional barcodes presented in black and white mosaic patterns that stores information read by smartphones or devices with in-built cameras [18]. QR Code carries data both horizontally and vertically, unlike barcodes which are in 1-D. This allows information encoded to be scanned in any direction, as well as enabling the storage of large amounts of information. Data can be restored even if the symbol is partially unreadable or damaged. QR code technology to transmit information through its higher data storage capacity, lower implementation cost, technical simplicity, widespread use, and availability [19]. Access to the encoded information in QR code technology is through free programs and the decoding is done using camera-equipped smartphones. Authentication procedures are relatively easier to implement using QR code technology, which provides security to users against unauthorized access. Authentication can be done with the use of a password and a QR code encrypted string consisting of the International Mobile Equipment Identity (IMEI) number of a user and digital watermarking [20]. QR code technology can access information in offline print media such as posters, cards, signs among others. This allows the transmission of information from one source to another at any time, with minimal restrictions.

QR codes are not a new concept, but not yet widespread in the medical world, but it is gaining attention. Most recently, QR code has been used to develop contact tracing applications and to maintain social distancing [21]. Most recently, Australia implemented contact tracing applications based on QR codes [22]. In Myanmar, QR code technology is used to monitor its citizens' health status and be able to inform the public about accurate information concerning the coronavirus [23]. QR code technology by its nature implements social distancing as information can be encoded, and it only requires a user to have a smart camera-equipped phone to decode the message thus minimizing human interaction. In China, a quick response code system was implemented to develop an electronic survey to check individuals' symptoms and record body temperature to minimize physical contact and interaction time between healthcare professionals and patients [24]. In addition, in China, QR code serves as a COVID-19 health status certificate and travel pass, with colour-codes representing low, medium, and high risk; individuals with green codes are permitted to travel unrestricted [25], whereas individuals with red codes are required to self-isolate for 14 days. Thus, the implementation of QR codes in healthcare serves as a powerful solution in improving communication, transparency between healthcare providers, caregivers, and care recipients. Also, QR codes have been implemented in healthcare through education and training to increase participant engagement, promote just-in-time learning, simulation, and training support [26]. The increase of participants' engagement can be in the form of anatomy teaching, formative assessment, case-based learning. For instance, in the case of anatomy teaching, medical student's experience an anatomy specimen museum where QR codes are attached to a particular specimen and provide ease of access to additional contextual information.

2.2 *Application of Emerging Technologies for QR Code Apps in Healthcare Services Delivery During COVID-19*

a. Blockchain in QR Code technology

Blockchains are distributed digital ledgers of cryptographically signed transactions that are grouped into blocks, where each block is linked cryptographically to the previous one after being validated and undergoing a consensus decision [27]. This technology allows a decentralized environment or data management that has no central authority. It allows simultaneous secure transactions due to the use of cryptographic principles. Blockchain can be in the form of a record that continues to grow into a block, which is connected and secured using cryptographic techniques [28]. Blockchain technology uses both distributed ownership and distributed physical architecture involving a large set of computers. Distributed systems are used by several users, in which blockchain users can maintain their copy of a ledger (a collection of transactions in the blockchain). Its distributed design also means nodes are dispersed widely and geographically. However, a validation key is required in blockchain, to build a new block, there must be a reference to a previous block (how the actual blockchain is made), if a reference is not included in the new block, other nodes will reject it [29]. For instance, Cheng et al. [30] proposed a system that solves the problem of counterfeiting education certificates by creating digital certificate systems that were based on blockchain technology.

Blockchain and QR technologies have been used to develop applications in healthcare. For instance, blockchain technology has been applied to manage patients' medical data where each patients' data can have an audit trail of the permissions, authorization and data sharing between healthcare systems to ensure the integrity of medical data [31]. Patients' data are linked with their blockchain-based identity. Blockchain can also add security to data access for QR code-based applications to ensure security and improve remote access to medical data [32]. Blockchain can facilitate the data verification process on the data encoded on QR codes. QR code-based applications are structured almost same the way as the implementation of blockchain, and this is ideal for security in a transactional process of a decentralized and transparent network [33]. Although blockchain technology sometimes experiences some technical barriers related to data storage and distribution, data can be re-identified or compromised even though blockchain can encrypt data. The speed and scalability of a completely distributed system might be affected by blockchain [34].

b. Artificial intelligence in QR technology

This technology has the potential to improve hypothesis generation and hypothesis testing tasks within a system by revealing previously hidden trends in data. Machine learning expands on existing statistical techniques, utilizing methods that are not based on prior assumptions about the distribution of the data, and can find patterns in the data [35]. Also, Idrees et al. [36] proposed a navigation technique for the visually impaired to efficiently move around indoors using QR codes to find both the optimal path as well as the shortest path to a destination deduced from the current location the user might be in. QR codes have also been used as artificial landmarks where it exists as a localization system for mobile robots. For example, smart wheelchairs for indoor navigation and these landmarks are detected by a webcam oriented to the ceiling, each QR code contains the coordinates of the landmark in the working environment. QR-code-based positioning is a push service rather than a pull service, thus, the user and application ask for a position whenever needed rather than being constantly tracked [37]. The QR codes are affixed to a landmark where mobile phone users can scan and access data.

c. 5G technology in QR code-based apps

5G technology is the current evolution of wireless connectivity, which uses microwave frequencies to accommodate many simultaneous users [38]. 5G is characterized by low latency, high speed, enhanced high-resolution bandwidth, superior reliability, and less energy consumption. The speed of 5G is about 10–30Gps, while 4G is 300 Mbps. 5G latency is said to be as low as 1 ms [39]. 5G allows an increasing number of remote-end applications that requires a communication network powerful enough to connect patients, healthcare professionals, medical equipment, and information sharing effectively. This can enhance the decoding and redirection of QR encoded information, this means retrieval and access to information on the internet would be fast for QR code-based systems due to the connection speed. 5G technology capability to connect devices remotely at a high speed, has enabled medical devices to become real-time connected devices used in different sectors in the health systems, such as wearable sensors to remotely monitor COVID-19 patients [40]. 5G has made it possible for virtual devices and virtual systems in health care, connected to the cloud to help patients with their treatments in real-time in things such as rehabilitation, remote operations as well as diagnosis. Immersive data traffic and system configuration, through high-speed technology, speeds up the process of decision making and location access. For instance, in China, 5G technology significantly transformed its response mechanism to the COVID-19 pandemic by providing better assistance to the frontline staff and facilitating improved virus tracking, patient monitoring, data collection, analysis and health care services [41]. Health care services delivered through 5G technology in China include online surveys, QR code prevention and control apps [42] as well as online mental health services to manage psychological health problems such as anxiety and depression, home delivery services and services for patients with chronic diseases [43].

d. Internet of Things (IoT) in QR code-based apps

The Internet of Things is defined as a scheme of interconnected computing tactics, digital, and mechanical devices possessing the capability of transmission of data over the defined network without having any human involvement at any level [44]. The IoT gateway utilizes security tokens to authenticate devices and services. Since QR technology is widely used for the authentication of users, IoT has the capability of encrypting transmitted data between the devices and IoT gateways and from there to the cloud. These devices capture, monitor, and transmit data to a public or private cloud to facilitate a new level of convenient and efficient automation [45]. IoT supports secure authentication between the scanning device and the device being scanned through QR codes. Since QR code is used to transmit encoded information. IoT facilitates such devices to share information via a wireless connection through the QR code-based mutual authentication protocol for the Internet of Things [46]. During COVID-19, there are several QR code-based applications deployed in the IoT environment to tackle the pandemic. For instance, QR code-based system, e-Class system was developed and deployed in IoT setup to ensure that students attend classes consistently, as well as keeping track of student academic performance [47].

e. Internet of Medical Things in QR code-based apps

Internet of Medical Things (IoMT) has been utilized for collecting diversified types of emotional and physical health-related data using smart wearable devices. Such smart sensory devices have been significantly used to remotely collect patients data such as body temperature, blood pressure, motion, and blood glucose during the COVID-19 pandemic [48]. These devices use sensors such as ECG sensor and EEG sensor to perform multiple functions including tracking COVID-19 patients [39], remote health monitoring and exigency warning [49]. In Japan, Hong Kong and Singapore hospitals have adopted the QR code technology where patients' data and hospital location are encoded in a QR code printed on a wristband [50]. Test tubes, medical equipment and drug packages, prescriptions are printed with QR codes for authenticity. In China, QR code-based health system was developed and first used in Hangzhou as an electronic voucher to grant permission for an individual to enter or exit a populated public space as well as permission to move from one area to the next within the region [51]. However, the implementation of the health QR code has increased the risk of social isolation with the population of China considered as old people [52]. The system relies heavily on smartphones which probably leave out older people without access to smartphones. Another QR code system that has been prominently used in China is the symptom checker. Each QR code (for an individual) is a health status certificate that is color-coded to serve the purpose to easily identify a person that should be in quarantine or isolation facilities [25].

f. Big data in QR code-based apps

Big data are complex data sets that traditional data processing systems cannot efficiently and economically store, manage, or process. Big data technology supports variety of healthcare services such as health data collection, disease monitoring, developing clinical decision support systems, and health management [53]. In the context of COVID-19, several digital tools including contact tracing apps and smart wearable devices continuously collect a vast amount of health data that could be used for mapping purposes, visualization, and most importantly, for effective decision making. For instance, big data together with computational algorithms have been used for modelling virus transmission, aiding infection control measures and emergency response analyses required during local or international disease outbreaks

[54]. QR technology has been used to develop vaccination certificates or immunity passports as well as contact tracing applications that generate massive data for aiding infection prevention and control measures in many countries including China, Taiwan, New Zealand and South Africa [11, 55].

g. Fog computing in QR code-based apps

Fog computing is an architecture that brings closer to the end-user the distribution of computation, communication, control and storage services [56]. This technology is based on remote cloud servers that are used to store and process large data collected from sensor nodes. Fog computing acts as an intermediary between cloud computing and end-users. It provides storage and computing services closer to end devices for real-time analysis. Fog computing's latency can enhance QR code's real-time processing because of instant access of services to end-users, while cloudlets enable improved privacy and reduced latency, bandwidth, scalability, reliability, and energy efficiency [57].

3 Issues Around the Use of QR Code-Based Apps in Healthcare Service Delivery

As mobile technologies increasingly becoming ubiquitous and pervasive, the adoption of QR code technology increases rapidly. This is evident by the adoption of the QR codes which grows rapidly during past years and the number of users increases exponentially, due to its features like high data storage capacity, fast scanning, error-correction, direct marking, and ease of use. Quick response technology has been adopted in various application domains including medical education and training [26], digital payment systems, digital marketing, and healthcare applications. For instance, QR code has been used to store case histories in maxillofacial radiology [58], safer use of medications by elderly patients [59] and patient instructions following orthopaedic cast application [60]. However, QR code is not immune to security threats and other factors that influence their adoption. There are several factors influence how the public accepts or refrain from using QR code-based apps. These factors include the adhesion of the population, regulatory policies, digital inequality, and ethical issues [61]. Acceptability depends on how leaders mobilize the new knowledge acquired with the shift in technological advancements to fight COVID-19.

a. Data Regulations

Concerns such as whether COVID-19 related data collected using QR code-based apps during the pandemic will be deleted or kept for other purposes after COVID-19 raises issues pertaining to regional and international health regulations [62]. This calls for a clear, legal and regulatory policy as well as frameworks for regional and international health data sharing post-COVID-19. However, the data captured during the pandemic can be used in future for developing robust and feasible health solutions to prepare for other pandemics in the future. Data regulations should specify data ownership, security, standards, format, and storage (centralized and decentralized) [63]. For instance, in centralized applications, data is collected, pseudonymized and send to a central database managed by an administrator or agency [64]. The decentralized application, however, makes use of users' storage to keep the collected data. Liability between the two is the access to the information, for example, the centralized approach means data is "owned" by or rather goes through the agency with which it is stored. In such circumstances, strict transparency about where the data are drawn from, public scrutiny of the process, and strong legislative protections against misuse like in South Korea [65].

b. Scalability

In the post-deployment of the QR code-based system, some parameters determine the scalability of a system. These can be summarized as; the number of users adopting the system, adding system features as well as system performance under severe workloads. These parameters summarize things like traffic, the number of computations done on both users' phones and the backend upon QR code requirement. Amid COVID-19, the system needs to be highly scalable to incorporate adding features, for example, some countries improved contact tracing apps to generate vaccination certificates or immunity passports [66]. If a system is not used or adopted, it is rendered as not scalable to the public and/or to users. Users adopt a system that has been reviewed as secure, therefore, scalability is also dependent on technical limitations such as highly skilled manpower to ensure data security and encryption while developing, deploying, configuring and maintaining a system [13]. A system should win users trust in terms of usability and privacy protection [67].

c. Security and privacy

QR codes require data encryption to ensure data protection and security. The fact that devices communicate through codes generated rather than the actual transmission of data is an upside for security reasons related to QR codes. Moreover, humans cannot read the code or decode it by simply looking at it, they can only get access to the information through QR code reader software. However, QR codes can be manipulated and compromise the security of data encoded in the code through phishing, fraud, and attacking the reader software [68]. QR code manipulation can be used to redirect users to sites or information and possibly tamper with the integrity of data encoded in the QR code leading to vulnerabilities and malicious attacks [69]. Also, the interconnectedness of digital solutions makes the systems vulnerable to passive and active attacks. Therefore, security standards, data and communication link encryption should be clearly defined to ensure data confidentiality, integrity and availability of the systems. Also, data standardization and health data protection should be clearly defined. Regulators should encourage the development of consent-based QR code-based digital solutions such as COVID-19 contact tracing apps, immunity passports and digital vaccination certificates that can be accessed in a secure, verifiable, and privacy-preserving way.

d. Policies and regulatory frameworks

The adoption of QR code-based health apps could be affected by different health policies and regulatory frameworks and policies in different countries. The absent framework, global standards and policies guiding the international and regional integration and synchronization of digital solutions for sharing of COVID-19 health data [9] such as vaccination certificates retards the adoption of QR-code systems in healthcare. There is a need for setting up global standards as a roadmap to guide the development and deployment of effective digital solutions in case of public health emergencies such as COVID-19. Regional and international regulatory authorities should be involved in public and private sector initiatives, policies, guidelines and develop a framework guiding the implementation of COVID-19 digital certificates. Regular consultation with end-users, governments, and technology solution providers through regional public–private sector initiatives.

e. Technology

There is a huge technological gap between developed and developing countries in healthcare services delivery through digital health technologies [70]. The digital gap is exacerbated by various factors including low budgetary support [71], lack uniform and regular funding for technological innovations and robust e-health policies [72]. This may affect scalability, interoperability, data management of health data at the regional and international levels. To alleviate some of these challenges, there is a need for private and public partnerships and investments to improve technological infrastructure.

4 Ethical Issues Emanating from QR Code-Based Applications

Digital applications linked with the recent combat against COVID-19 have posed ethical and legal challenges to suspected and infected individuals [13]. Tracking the population's location data has fed into insecurities that the public has in mass surveillance, which could lead to ethically unjustified measures and stigmatization [61]. However, the QR code health system is not immune to ethical issues such as security, privacy, monitoring, over-surveillance, and discrimination. Surveillance of individuals has been a major issue, since the advent of highly individual and contextualized surveillance methods during public emergency [73]. For instance, the use of contact tracing apps and issuance of COVID-19 vaccination certificates pose considerable scientific, practical, equitable, ethical and legal concerns. Among other challenges, the issuance and sharing of COVID-19 data raised ethical concerns since data will be accessed by many regulatory authorities in various jurisdictions without predefined international standards and regulations. This may violate ethical values such as honesty, truthful consent, transparency, security and privacy. Therefore, the use of QR code apps (contact tracing and vaccination information) in health systems raises the following ethical concerns such as; will the privacy protection of people be guaranteed? and COVID-19 data collected through QR code-based contact tracing apps and vaccination certificates, or immunity passports be used for their intended purpose?

Due to the existing socio-economic disparities among different populations especially in developing countries affect the adoption and rolling out of digital technology to tackle COVID-19 due to poor internet connection and speed, infrastructure, and computing devices. Disadvantaged communities might not have access to QR code-based apps because of the digital divide. Rolling out of COVID-19 digital solutions should not assume that the whole global populations have universal access to digital technologies, yet the gap still exists between technology access and utilization among vulnerable populations [73]. Thus, socio-economic inequalities contribute to healthcare disparities.

5 Conclusion

Quick response technology has been gaining attention and adopted in many disciplines from education, banking and finance, and recently in healthcare services. Therefore, it seems that it is quite promising in health and solves many issues to do with authentication and security of patient data as well as patient data distribution amongst stakeholders. From the discussion done in this chapter, it seems very possible that the QR code technology can be applied in health information systems to monitor the migration patterns of people, validate COVID-19 test results and vaccination certificates. However, care and measures should be taken into consideration to avoid misuse and protect users' data. Future work should focus on developing feasible digital tools to cater for feature phones and most importantly, alternative ways of providing services to the populace without access to digital devices is required.

References

1. Wu, Y.C., Chen, C.S., Chan, Y.J.: The outbreak of COVID-19: an overview, /pmc/articles/PMC7153464/ (2020). https://doi.org/10.1097/JCMA.0000000000000270
2. Pradhan, D., Biswasroy, P., Kumar Naik, P., Ghosh, G., Rath, G.: A review of current interventions for COVID-19 prevention (2020). https://doi.org/10.1016/j.arcmed.2020.04.020.
3. Lewnard, J.A., Lo, N.C.: Scientific and ethical basis for social-distancing interventions against COVID-19. https://www.cdc.gov/ (2020). https://doi.org/10.1016/S1473-3099(20)30190-0
4. Lurie, N., Saville, M., Hatchett, R., Halton, J.: Developing Covid-19 vaccines at pandemic speed. N. Engl. J. Med. **382**, 1969–1973 (2020). https://doi.org/10.1056/nejmp2005630
5. Forni, G., Mantovani, A., Forni, G., Mantovani, A., Moretta, L., Rappuoli, R., Rezza, G., Bagnasco, A., Barsacchi, G., Bussolati, G., Cacciari, M., Cappuccinelli, P., Cheli, E., Guarini, R., Bacci, M.L., Mancini, M., Marcuzzo, C., Morrone, M.C., Parisi, G., Pasquino, G., Patrono, C., Curzio, A.Q., Remuzzi, G., Roncaglia, A., Schiaffino, S., Vineis, P.: COVID-19 vaccines: where we stand and challenges ahead (2021). https://doi.org/10.1038/s41418-020-00720-9

6. Thiagarajan, K.: Why is India having a covid-19 surge? BMJ **373**, n1124 (2021). https://doi.org/10.1136/bmj.n1124
7. Dzinamarira, T., Dzobo, M., Chitungo, I.: COVID-19: A perspective on Africa's capacity and response (2020) https://onlinelibrary.wiley.com/doi/full/10.1002/jmv.26159
8. Chitungo, I., Mhango, M., Mbunge, E., Dzobo, M., Dzinamarira, T.: Digital technologies and COVID-19: reconsidering lockdown exit strategies for Africa. Pan Afr. Med. J. **39** (2021). https://doi.org/10.11604/pamj.2021.39.93.29773
9. Mbunge, E., Dzinamarira, T., Fashoto, S.G., Batani, J.: Emerging technologies and COVID-19 digital vaccination certificates and passports, /pmc/articles/PMC8103710/ (2021). https://doi.org/10.1016/j.puhip.2021.100136
10. Loomba, S., de Figueiredo, A., Piatek, S.J., de Graaf, K., Larson, H.J.: Measuring the impact of COVID-19 vaccine misinformation on vaccination intent in the UK and USA. Nat. Hum. Behav. **5**, 337–348 (2021). https://doi.org/10.1038/s41562-021-01056-1
11. Mbunge, E., Akinnuwesi, B., Fashoto, S.G., Metfula, A.S., Mashwama, P.: A critical review of emerging technologies for tackling COVID-19 pandemic (2021). https://onlinelibrary.wiley.com/doi/full/10.1002/hbe2.237
12. He, W., Zhang, Z. (Justin), Li, W.: Information technology solutions, challenges, and suggestions for tackling the COVID-19 pandemic. Int. J. Inf. Manag. **57**, 102287 (2021). https://doi.org/10.1016/j.ijinfomgt.2020.102287
13. Mbunge, E.: Integrating emerging technologies into COVID-19 contact tracing: opportunities, challenges and pitfalls. Diabetes Metab. Syndr. Clin. Res. Rev. **14**, 1631–1636 (2020). https://doi.org/10.1016/j.dsx.2020.08.029
14. Voo, T.C., Reis, A.A., Thomé, B., Ho, C.W.L., Tam, C.C., Kelly-Cirino, C., Emanuel, E., Beca, J.P., Littler, K., Smith, M.J., Parker, M., Kass, N., Gobat, N., Lei, R., Upshur, R., Hurst, S., Munsaka, S.: Immunity certification for COVID-19: Ethical considerations. Bull. World Health Organ. **99**, 155–161 (2021). https://doi.org/10.2471/BLT.20.280701
15. Mbunge, E., Fashoto, S.G., Batani, J.: COVID-19 digital vaccination certificates and digital technologies: lessons from digital contact tracing apps. SSRN Electron. J. (2021). https://doi.org/10.2139/ssrn.3805803
16. Dye, C., Mills, M.C.: COVID-19 vaccination passports. Science (80-.). 371, (2021). https://doi.org/10.1126/SCIENCE.ABI5245
17. Mithani, S.S., Bota, A.B., Zhu, D.T., Wilson, K.: A scoping review of global vaccine certicate solutions for COVID-19. https://doi.org/10.21203/rs.3.rs-334258/v2
18. Sharara, S., Radia, S.: Quick Response (QR) codes for patient information delivery: a digital innovation during the coronavirus pandemic (2021) https://doi.org/10.1177/14653125211031568
19. Yan, L.Y., Tan, G.W.H., Loh, X.M., Hew, J.J., Ooi, K.B.: QR code and mobile payment: the disruptive forces in retail. J. Retail. Consum. Serv. **58**, 102300 (2021). https://doi.org/10.1016/j.jretconser.2020.102300
20. Pan, J.S., Sun, X.X., Chu, S.C., Abraham, A., Yan, B.: Digital watermarking with improved SMS applied for QR code. Eng. Appl. Artif. Intell. **97**, 104049 (2021). https://doi.org/10.1016/j.engappai.2020.104049
21. Lee, E., Chen, Y.-Y., McDonald, M., O'Neill, E.: Dynamic response systems of healthcare mask production to COVID-19: a case study of Korea. Systems **8**, 18 (2020). https://doi.org/10.3390/SYSTEMS8020018
22. Howell, B., Potgieter, P.H.: A tale of two contact-tracing apps—comparing Australia's CovidSafe and New Zealand's NZ Covid Tracer. Digit. Policy, Regul. Gov. (2021). ahead-of-print. https://doi.org/10.1108/DPRG-06-2020-0075
23. Aung, M.N., Stein, C., Chen, W.-T., Garg, V., Sitepu, M.S., Thu, N.T.D., Gundran, C.P.D., Hassan, M.R., Suthutvoravut, U., Soe, A.N., Nour, M., Gyi, K.K., Brandl, R., Yuasa, M.: Community responses to COVID-19 pandemic first wave containment measures: a multinational study. J. Infect. Dev. Ctries **15**, 1107–1116 (2021). https://doi.org/10.3855/jidc.15254

24. Faggiano, A., Carugo, S.: Can the implementation of electronic surveys with quick response (QR) codes be useful in the COVID-19 era? Int. J. Epidemiol. **49**, 1732–1733 (2020). https://doi.org/10.1093/IJE/DYAA170
25. Whitelaw, S., Mamas, M.A., Topol, E., Van Spall, H.G.C.: Applications of digital technology in COVID-19 pandemic planning and response. Lancet Digit. Health **2**, e435–e440 (2020). https://doi.org/10.1016/S2589-7500(20)30142-4
26. Karia, C.T., Hughes, A., Carr, S.: Uses of quick response codes in healthcare education: a scoping review. BMC Med. Educ. **191**. 19, 1–14 (2019). https://doi.org/10.1186/S12909-019-1876-4
27. Yaga, D., Mell, P., Roby, N., Scarfone, K.: Blockchain Technology Overview (2019). https://doi.org/10.6028/nist.ir.8202
28. Haddouti, S. El, Ech-Cherif El Kettani, M.D.: Analysis of identity management systems using blockchain technology. In: Proceedings of 2019 International Conference on Advanced Communication Technologies and Networking, CommNet 2019 (2019). https://doi.org/10.1109/COMMNET.2019.8742375
29. Halim, E., Subagio, M.A., Halim, D.D., Hebrard, M.: The implementation of supply chain management in the N95 respirator product by using blockchain technology. Int. Conf. Inf. Manag. Technol. 539–544 (2021). https://doi.org/10.1109/ICIMTECH53080.2021.9535077
30. Cheng, J.C., Lee, N.Y., Chi, C., Chen, Y.H.: Blockchain and smart contract for digital certificate. In: Proceedings of 4th IEEE International Conference on Applied System Innovation, ICASI 2018, pp. 1046–1051 (2018). https://doi.org/10.1109/ICASI.2018.8394455
31. Tian, H., He, J., Ding, Y.: Medical data management on blockchain with privacy. J. Med. Syst. **432**(43), 1–6 (2019). https://doi.org/10.1007/S10916-018-1144-X
32. Rakib, G.A., Saiful Islam, M., Rahman, M.A., Maruf Syed, A., Hossain, M.S., Alrajeh, N.A., Saddik, A. El: DeepHealth: a secure framework to manage health certificates through medical IoT, blockchain and deep learning, 1–6 (2021). https://doi.org/10.1109/MEMEA52024.2021.9478691
33. Gupta, A., Khanna, P., Kumar, S.: A hybrid blockchain-secured elderly healthcare environment. Blockchain 5G-enabled IoT, 401–439 (2021). https://doi.org/10.1007/978-3-030-67490-8_16
34. Scherer, M.: Performance and scalability of blockchain networks and smart contracts (2017)
35. Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R., Muharemagic, E.: Deep learning applications and challenges in big data analytics. J. Big Data **21**(2), 1–21 (2015). https://doi.org/10.1186/S40537-014-0007-7
36. Idrees, A., Iqbal, Z., Ishfaq, M.: An efficient indoor navigation technique to find optimal route for blinds using QR codes. In: Proceedings of 2015 10th IEEE Conference on Industries Electronic Application. ICIEA 2015, pp. 690–695 (2015). https://doi.org/10.1109/ICIEA.2015.7334197
37. Basiri, A., Amirian, P., Winstanley, A.: The Use of Quick Response (QR) codes in landmark-based pedestrian navigation (2014). https://doi.org/10.1155/2014/897103
38. Dananjayan, S., Raj, G.M.: 5G in healthcare: how fast will be the transformation? Irish J. Med. Sci. (1971 -) 2020 1902. **190**, 497–501 (2020). https://doi.org/10.1007/S11845-020-02329-W
39. Mbunge, E., Fashoto, S.G., Akinnuwesi, B., Metfula, A., Simelane, S., Ndumiso, N.: Ethics for integrating emerging technologies to contain COVID-19 in Zimbabwe. Hum. Behav. Emerg. Technol. (2021). https://doi.org/10.1002/HBE2.277
40. Mbunge, E., Millham, R.C., Sibiya, M.N., Fashoto, S.G., Akinnuwesi, B., Simelane, S., Ndumiso, N.: Framework for ethical and acceptable use of social distancing tools and smart devices during COVID-19 pandemic in Zimbabwe. Sustain. Oper. Comput. **2**, 190–199 (2021). https://doi.org/10.1016/J.SUSOC.2021.07.003
41. Chamola, V., Hassija, V., Gupta, V., Guizani, M.: A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, Blockchain, and 5G in managing its impact. IEEE Access **8**, 90225–90265 (2020). https://doi.org/10.1109/ACCESS.2020.2992341
42. Jiancheng: The role of health technology and informatics in a global public health emergency: practices and implications from the COVID-19 pandemic. JMIR Med. Inf. **8**(7), e19866 (2020). https//medinform.jmir.org/2020/7/e19866. https://doi.org/10.2196/19866

43. Qing, Zhou, J., Wu, H.: Using information technology to manage the COVID-19 pandemic: development of a technical framework based on practical experience in China. JMIR Med Inf. **8**(6), e19515 (2020). https//medinform.jmir.org/2020/6/e19515. https://doi.org/10.2196/19515
44. Singh, R.P., Javaid, M., Haleem, A., Suman, R.: Internet of things (IoT) applications to fight against COVID-19 pandemic. Diabetes Metab. Syndr. Clin. Res. Rev. **14**, 521–524 (2020). https://doi.org/10.1016/J.DSX.2020.04.041
45. Bai, L., Yang, D., Wang, X., Tong, L., Zhu, X., Zhong, N., Bai, C., Powell, C.A., Chen, R., Zhou, J., Song, Y., Zhou, X., Zhu, H., Han, B., Li, Q., Shi, G., Li, S., Wang, C., Qiu, Z., Zhang, Y., Xu, Y., Liu, J., Zhang, D., Wu, C., Li, J., Yu, J., Wang, J., Dong, C., Wang, Y., Wang, Q., Zhang, L., Zhang, M., Ma, X., Zhao, L., Yu, W., Xu, T., Jin, Y., Wang, X., Wang, Y., Jiang, Y., Chen, H., Xiao, K., Zhang, X., Song, Z., Zhang, Z., Wu, X., Sun, J., Shen, Y., Ye, M., Tu, C., Jiang, J., Yu, H., Tan, F.: Chinese experts' consensus on the Internet of Things-aided diagnosis and treatment of coronavirus disease 2019 (COVID-19). Clin. eHealth **3**, 7–15 (2020). https://doi.org/10.1016/J.CEH.2020.03.001
46. Marktscheffel, T., Gottschlich, W., Popp, W., Werli, P., Fink, S.D., Bilzhause, A., De Meer, H.: QR code based mutual authentication protocol for Internet of Things. In: WoWMoM 2016—17th International Symposium a World Wireless, Mobile Multimedia Networks (2016). https://doi.org/10.1109/WOWMOM.2016.7523562
47. Bakar, S.A., Salleh, S.N.M., Rasidi, A., Tasmin, R., Hamid, N.A.A., Nda, R.M., Rusuli, M.S.C.: Integrating QR code-based approach to university e-Class system for managing student attendance. Adv. Intell. Syst. Comput. **1158**, 379–387 (2021). https://doi.org/10.1007/978-981-15-4409-5_34
48. Xiong, L., Zhong, X., Xiong, N.N., Liu, R.W.: QR-3S: a high payload QR code secret sharing system for industrial internet of things in 6G networks. IEEE Trans. Ind. Inf. **17**, 7213–7222 (2021). https://doi.org/10.1109/TII.2020.3044006
49. Pratap Singh, R., Javaid, M., Haleem, A., Vaishya, R., Ali, S.: Internet of Medical Things (IoMT) for orthopaedic in COVID-19 pandemic: roles, challenges, and applications. J. Clin. Orthop. Trauma. **11**, 713–717 (2020). https://doi.org/10.1016/J.JCOT.2020.05.011
50. Koo, B., Moon, T., Kim, H.: MurQRI: encrypted multi-layer QR codes for electronic identity management. Commun. Comput. Inf. Sci. **1383**, 98–108 (2020). https://doi.org/10.1007/978-3-030-72725-3_7
51. Liu, W., Yue, X.-G., Tchounwou, P.B.: Response to the COVID-19 epidemic: the Chinese experience and implications for other countries. Int. J. Environ. Res. Public Heal. **17**, 2304 (2020). https://doi.org/10.3390/IJERPH17072304
52. Shao, P., Xu, Y., Pan, C.W.: Factors associated with and prevalence of depressive features amongst older adults in an urban city in eastern China. South Afr. J. Psychiatr. **23** (2017). https://doi.org/10.4102/SAJPSYCHIATRY.V23I0.1064
53. Jun, Wang, J., Nicholas, S., Maitland, E., Fan, Q.: Application of big data technology for COVID-19 prevention and control in China: lessons and recommendations. J. Med. Internet Res. **22**(10), e21980 (2020). https//www.jmir.org/2020/10/e21980. https://doi.org/10.2196/21980
54. Joy, M.R., Bairavel, S., Dhanalakshmi, R.: Implementing QR code–based contact tracing framework. In: 2021 International Conference on System Computer Automation Network, pp. 1–6 (2021). https://doi.org/10.1109/ICSCAN53069.2021.9526486
55. Ichiro, Wang, S., Guo, Y., Zhuang, W.: A QR code–based contact tracing framework for sustainable containment of COVID-19: evaluation of an approach to assist the return to normal activity. JMIR Mhealth Uhealth **8**(9), e22321 (2020). https//mhealth.jmir.org/2020/9/e22321. https://doi.org/10.2196/22321
56. Madsen, S.S., Santos, A.Q., Jørgensen, B.N.: A QR code based framework for auto-configuration of IoT sensor networks in buildings. Energy Inf. **42**(4), 1–19 (2021). https://doi.org/10.1186/S42162-021-00152-W
57. Manzoor, A., Shah, M.A., Khattak, H.A., Din, I.U., Khan, M.K.: Multi-tier authentication schemes for fog computing: architecture, security perspective, and challenges. Int. J. Commun. Syst. e4033 (2019). https://doi.org/10.1002/DAC.4033

58. Shakil, Karteek, D., Spoorti, K., Jose, M.: Quick response code in Oral and maxillofacial radiology. J. Oral Maxillofac. Radiol. **2**, 95 (2014). https://doi.org/10.4103/2321-3841.144696
59. Mira, J.J., Guilabert, M., Carrillo, I., Fernández, C., Vicente, M.A., Orozco-Beltrán, D., Gil-Guillen, V.F.: Use of QR and EAN-13 codes by older patients taking multiple medications for a safer use of medication. Int. J. Med. Inform. **84**, 406–412 (2015). https://doi.org/10.1016/J.IJMEDINF.2015.02.001
60. AT, G., G, F., PAV, G., M, B., RJ, K., RG, M.: A novel use of QR code stickers after orthopaedic cast application. **99**, 476–478 (2017). https://doi.org/10.1308/RCSANN.2017.0070
61. Georgieva, I., Beaunoyer, E., Guitton, M.J.: Ensuring social acceptability of technological tracking in the COVID-19 context. Comput. Human Behav. **116**, 106639 (2021). https://doi.org/10.1016/J.CHB.2020.106639
62. Parker, M.J., Fraser, C., Abeler-Dörner, L., Bonsall, D.: Ethics of instantaneous contact tracing using mobile phone apps in the control of the COVID-19 pandemic. J. Med. Ethics **46**, 427–431 (2020). https://doi.org/10.1136/MEDETHICS-2020-106314
63. Idrees, S.M., Nowostawski, M., Jameel, R.: Blockchain-based digital contact tracing apps for COVID-19 pandemic management: issues, challenges, solutions, and future directions. JMIR Med. Inf. **9** (2021). https://doi.org/10.2196/25245
64. Morley, J., Cowls, J., Taddeo, M., Floridi, L.: Ethical guidelines for COVID-19 tracing apps. Nature 5827810. **582**, 29–31 (2020). https://doi.org/10.1038/d41586-020-01578-0.
65. Martinez-Martin, N., Wieten, S., Magnus, D., Cho, M.K.: Digital contact tracing, privacy, and public health. Hastings Cent. Rep. **50**, 43–46 (2020). https://doi.org/10.1002/HAST.1131
66. Dar, A.B., Lone, A.H., Zahoor, S., Khan, A.A., Naaz, R.: Applicability of mobile contact tracing in fighting pandemic (COVID-19): Issues, challenges and solutions. Comput. Sci. Rev. **38**, 100307 (2020). https://doi.org/10.1016/J.COSREV.2020.100307
67. Cho, H., Ippolito, D., Yu, Y.W.: Contact tracing mobile apps for COVID-19: privacy considerations and related trade-offs (2020)
68. Choudhury, Z.H., Rabbani, M.M.A.: Biometric passport for national security using multibiometrics and encrypted biometric data encoded in the QR Code **15**, 199–229 (2019). https://doi.org/10.1080/19361610.2019.1630226
69. Wahsheh, H.A.M., Luccio, F.L.: Security and privacy of QR code applications: a comprehensive study, general guidelines and solutions. Inf. **11**, 217 (2020). https://doi.org/10.3390/INFO11040217
70. Lee, S.M., Lee, D.H.: Opportunities and challenges for contactless healthcare services in the post-COVID-19 Era. Technol. Forecast. Soc. Change **167**, 120712 (2021). https://doi.org/10.1016/J.TECHFORE.2021.120712
71. Chitungo, I., Mhango, M., Dzobo, M., Denhere, K., Chimene, M., Musuka, G., Dzinamarira, T.: Towards virtual doctor consultations: A call for the scale-up of telemedicine in sub-Saharan Africa during COVID-19 lockdowns and beyond. Smart Health **21**, 100207 (2021). https://doi.org/10.1016/J.SMHL.2021.100207
72. Dubov, A., Shoptawb, S.: the value and ethics of using technology to contain the COVID-19 epidemic **20**, W7–W11 (2020). https://doi.org/10.1080/15265161.2020.1764136
73. Lucivero, F., Hallowell, N., Johnson, S., Prainsack, B., Samuel, G., Sharon, T.: COVID-19 and contact tracing apps: ethical challenges for a social experiment on a global scale. J. Bioethical Inq. **174**(17), 835–839 (2020). https://doi.org/10.1007/S11673-020-10016-9

Optimal Testing Strategies for Infectious Diseases

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Abstract Screening tests for infectious diseases is a problem typically addressed in the field of Medicine and Epidemics. However, as the SARS-CoV-2 pandemic emerged, it became clear that there is no globally accepted strategy for optimizing such procedures, e.g. in international transportation and border checks, which policy makers can employ. In this study, the general problem of developing optimal testing strategies for infectious diseases is explored under the scope of Game Theory, sampling and estimation methods from classic Statistics, as well as Bayesian methods for the proper treatment of posterior updates, leading to the benefits of employing Machine Learning for data-driven structural risk minimization. Six main guidelines are established by this work, dictating estimated variance of prevalence and associated risk as the main minimization target, in terms of both a criterion for inflow quotas allocation between population groups, as well as optimal posterior updates via classic confidence intervals and Bayesian methods. As a result, it is established that minimum infection risk, not optimal resource allocation, is the real challenge and top priority in formalizing optimal screening strategies for such risk mitigation policies.

Keywords Epidemics · SARS-CoV-2 · Screening methods · Testing strategies · Game theory · Machine learning · Bayesian methods

1 Introduction

The SARS-CoV-2 pandemic that characterized 2020 was the most crucial factor in revisiting common practices and re-establishing risk-mitigation policies in terms of population screening for infectious diseases. As of September 2021, world-wide statistics [10] show that a third pandemic surge is at its peak and there are more

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than 219 million confirmed cases, with more than 4.55 million deaths directly associated with the COVID disease. This is perhaps the most severe health emergency since the Spanish flu a century ago. Although this virus seems to exhibit patterns of droplet rather than aerosol transmission, its rate is very high and it combined with an incubation period of 4–7 days [24]. Due to international flights, this 'window of opportunity' is extremely crucial for the virus to spread undetected in asymptomatic carriers. The recent 'delta' variant seems to exhibit even longer incubation period, perhaps up to 7–8 days, while the virus itself is more contagious than the original strain, making it even more dangerous.

Testing strategies is perhaps the single most valuable tool for the containment of the virus spread, especially between countries and when international travel bans are to be lifted. However, there are theoretical and practical aspects that make perfect screening impossible, leaving the decision makers with the crucial but ill-defined challenge of how to introduce risk-mitigation plans, based on imperfect information, time delays and limited resources.

With the SARS-CoV-2 pandemic still surging almost two years after its first appearance in Wuhan (November 2019), the current focus in testing strategies worldwide is towards long-term epidemic monitoring within a country, i.e., as part of mitigation policies for restoring normal economic activities and avoiding strict lockdowns. There are numerous guidelines from the international health organizations like CDC (USA), ECDC (EU) and WHO [11–14, 43], as well as from the research community [6, 28, 36]. However, there are only few works addressing the challenge of optimizing testing in border checks, i.e., very short-term screening human flows (travellers, within 1 h at most) using only limited resources (number of test kits per day per entry point). These approaches include mostly adaptations w.r.t. incidence rates [2, 21, 33], statistical models on prevalence [9, 20], bandit formulations for 'hit' rate optimization [5, 27], etc. There are only few game-theoretic approaches for modelling the evolution of the outbreak, the effects of the individual behaviours and the mitigation policies [3, 7, 35]. However, none of these approaches address the challenge of combining incidence rates, inherent cost for 'missed' cases and the posterior (after testing) probabilities for healthy/infected individuals, specifically for very short-term screening human flows in border crossings between countries, which essentially is the driving factor for turning national-level epidemics into a global pandemic. Moreover, no such approach is available as a well-defined framework based on mathematical foundations and derived strategies.

In this work, the challenge of optimal testing strategies for infectious disease screening is treated in a unified way. Beginning from the problem under the viewpoint of Game Theory, the decision-making authority has to optimize its testing strategy for groups of individuals, partitioned on the basis of some inherent property, e.g. the country of origin, demographics, etc. Assuming a fixed capability on the base task of selecting 'safe' and 'non-safe' individuals, the game setup of player-against-Nature and the goal is to minimize the loss from improper allocation of increased and decreased rates of flow, which is typically associated to what is happening in screening gates between countries or between regions within the same country.

On top of the game-theoretic formalization of the testing strategies for the decision-making authority, their capability is further explored within the context of Sampling Theory and Estimation Theory. Since all estimations are based on sampled data and not perfect 'Oracle' view of the entire population, proper adjustments should be made to the properties that define the game-theoretic optimizations. Moreover, the inherent limitations and 'static' nature of the standard confidence interval methods are compared to the more rigorous and intuitive view of the Bayesian methods for optimal posterior updates of the corresponding probabilistic models.

Aggregating all these aspects of the screening tests during an epidemic, this work presents a proper formalization of each step in a constructive way and clearly defines their constraints. Section 2 defines the main task, which is the problem of optimizing the policies for screening tests; Sect. 3 provides the general game-theoretic framework, solution concepts and evidence-based adaptations; Sect. 4 extends this framework to multiple 'experts', also providing solution concepts and application to testing strategies; Sect. 5 describes the related theory for sampling, estimation and evidence-based posterior updates, including point statistics, confidence intervals and Bayesian methods; finally, Sect. 6 discusses further complications from having to cope with time-varying uncertainty in the evidence and counter-intuitive testing strategies for prompt containment of the disease, as well as some concluding remarks in Sect. 7.

2 Problem Statement

First of all, let us define the exact optimization task, which in general terms can be described with the two equivalent statements:

– *Minimize* the *risk* margin of *not identifying* infected individuals in a target group, i.e., the *cost* expectancy.
– *Maximize* the *safety* margin of *identifying* infected individuals in a target group, i.e., the *gain* expectancy.

In the first statement, 'cost' is referring to the probabilistic expectancy of the overall negative impact for the group from missed cases of infected individuals, which is associated to a risk margin, i.e., a 'miss' probability. Similarly, in the second statement, 'gain' is referring to the probabilistic expectancy of the overall positive impact for the group from detected cases of infected individuals, which is associated to a safety margin, i.e., a 'hit' probability. The two definitions can be considered equivalent in the sense that detecting and isolating infected individuals is always beneficial for the group. Hence, in the following analysis they are used interchangeably as needed, with complementary probabilities and outcomes.

3 Game-Theoretic Formalization

A very generic approach in formalizing the definition of this optimization setup is via Game Theory [18, 31, 34] . Specifically, a zero-sum game can be designed between 'Nature' that defines the (unknown) infected individuals and the checking 'authority' that tries to identify and isolate them, i.e., mitigate the negative impact of missed cases. In this setup, 'Nature' is typically the 'negative' player and the 'authority' is the 'positive' player; since 'Nature' is the stochastic factor out of any immediate control, 'authority' is of the main interest here and is typically associated to the positive-valued outcomes of the game. Hence, the second statement in Sect. 2 is the one that is preferred by default when defining probabilities ('hits') and outcomes ('gain').

Let C be the zero-sum 'checking' game according to the previous generic description of Sect. 2. Let N be the total number of individuals, either 'safe' (not infected) or 'non-safe' (infected), partitioned according to $L = \langle \ell_k \rangle$, $N = |\bigcup \ell_k|$, $k \in \{1, \ldots, |L|\}$, and with corresponding subset sizes n_k , $N = \sum_{k=1}^{|L|} n_k$. If p_k^s is the probability of an individual in group k being 'safe', then $p_k^{ns} = (1 - p_k^s)$ is the associated probability of an individual being 'non-safe' in that same group. With n_k being the size of group k, $c_k^s \geq 0$ is the marginal gain from each 'safe' individual and $-c_k^{ns} \leq 0$ is the marginal cost from each 'non-safe' individual, then the probabilistic expectancy (game value) from each group outcome is:

$$v_k(C) = n_k(p_k^s c_k^s - (1 - p_k^s)c_k^{ns}) \tag{1}$$

where c_k^s and c_k^{ns} can be considered as common for all subsets in L, thus can be used as c^s and c^{ns}, respectively, with k omitted.

Besides the p_k^s probability, n_k is the other crucial factor for determining the overall outcome of the game. In practice, there are two extreme options for the checking authority: (a) admitting all the n_k individuals in the group or (b) not admitting anyone of them. If subsets ℓ_k are fixed and cannot be partitioned further, then only these two extreme options are available and the task becomes discrete (combinatorial), i.e., selecting or discarding each ℓ_k from L. Option (b) is the pure strategy that always guarantees a non-negative outcome, but in practice this also comes with an associated cost of not admitting the 'safe' individuals. In terms of game C, there are two pure strategies for each player and four outcomes in total, as illustrated in Table 1. However, since the main interest here is to estimate the optimal strategy for the checking authority (rows) and the two extreme options can be merged taking $n_k \geq 0$, the corresponding target function for maximization is Eq. 1 restated as:

$$v_k(C) = n_k(p_k^s c^s - (1 - p_k^s)c^{ns}) \tag{2}$$

The optimization task defined by Eq. 2 is considered against all the subsets ℓ_k in partitioning L, i.e., for some fixed total sum $N = \sum_{k=1}^{|L|} n_k$ and the combined expectancy $v(C) = \sum_{k=1}^{|L|} v_k(C)$, regarding the partitioning into subsets $\ell_k \in L$ and

Table 1 Zero-sum 'checking' game C in complete 2-by-2 form

	p_k^s	$1 - p_k^s$
$n_k > 0$	$+c^s$	$-c^{ns}$
$n_k = 0$	$-c^s$	$+c^{ns}$

their corresponding sizes n_k. The exact aggregated maximization of $v(C)$ against partitioning L with subsets of sizes n_k is stated in Definition 1 for arbitrary sizes n_k and in Definition 2 for fixed sizes n_k (selection of indices k).

Definition 1 (*Optimal partitioning in game C with subsets of arbitrary sizes*) Let C be a zero-sum 'checking' game as described in Eq. 2, with $0 \leq p_k^s \leq 1$, $\{c^s, c^{ns}\} \geq 0$, $L = \langle \ell_k \rangle \neq \emptyset$, $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} n_k$. Then the combined expectancy $v(C) = \sum_{k=1}^{|L|} v_k(C)$, regarding the partitioning L into subsets ℓ_k of corresponding sizes n_k, is maximized with a specific set $\langle n_k \rangle = \{n_1, \ldots, n_{|L|}\}$:

$$\langle n_k \rangle : \arg\max_{n_k} \sum_{k=1}^{|L|} v_k(C) \tag{3}$$

If the partitioning L defines subsets of fixed size, then the problem becomes a discrete optimization task, with the target being the selection of a combination of $\ell_k inL$ that exhibit the maximum overall payoff, as Definition 2 states:

Definition 2 (*Optimal partitioning in game C with subsets of fixed sizes*) Let C be a zero-sum 'checking' game as described in Eq. 2, with $0 \leq p_k^s \leq 1$, $\{c^s, c^{ns}\} \geq 0$, $L = \langle \ell_k \rangle \neq \emptyset$, $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} n_k$. Then the combined expectancy $v(C) = \sum_{k=1}^{|L|} v_k(C)$, regarding the partitioning L into subsets ℓ_k of corresponding fixed sizes $n_k = \ell_k$, is maximized with a specific combination of indices k in the set $\langle n_k \rangle \in \{n_1, \ldots, n_{|L|}\}$:

$$\langle k \rangle : \arg\max_{k} \sum_{k=1}^{|L|} v_k(C) \tag{4}$$

Definitions 1 and 2 formalize the optimization task for the checking authority ('max' player) regarding the game C. In the first case the authority is free to adjust $\langle n_k \rangle$ freely with the only constraint being $n_k \geq 0$, i.e., enlarge or reduce each subset in the partitioning L. In the second case the subset sizes n_k are fixed and the authority can only adjust the selection of indices in $\langle k \rangle \in \{1, \ldots, |L|\}$. In both cases, the subset sizes n_k are constrained by the partitioning L, i.e., $N = \sum_{k=1}^{|L|} n_k$.

3.1 Solution Concepts

As stated previously, the obvious strategy for the checking authority in order to ensure $v(C) \nless 0$ is to set $n_k = 0, \forall\, k \in \{1, \ldots, |L|\}$, if there is such a valid option available. However, the most usual case is that the total sum $N = \sum_{k=1}^{|L|} n_k > 0$ is a fixed constraint, i.e., cannot be avoided or maybe not even reduced. This essentially makes the overall task for $v(C)$ against $\langle n_k \rangle$ a convex optimization problem in a continuous (Definition 1) or a discrete (Definition 2) space.

In order to see how $v(C)$ is maximized against n_k given p_k^s taking into account all k, Eq. 2 is applied to Eqs. 3 and 4 for the arbitrary or fixed sizes n_k, respectively. Intuitively, we expect that for $p_1^s \geq p_2^s \geq \ldots \geq p_{|L|}^s$, the obvious choice for $k \in \{1, \ldots, |L|\}$ is such that it maximizes the corresponding subset sizes, i.e., $n_1 \geq n_2 \geq \ldots \geq n_{|L|}$ while satisfying the constraint $N = \sum_{k=1}^{|L|} n_k > 0$. Lemma 1 and Theorem 1 provide the formal proofs for this optimizer.

Lemma 1 *Let C be a zero-sum 'checking' game as described in Definition 1, with $0 \leq p_k^s \leq 1$, $\{c^s, c^{ns}\} \geq 0$, $L = \langle \ell_k \rangle \neq \emptyset$, $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} n_k$. Let Θ be the indices defining the descending ordering of $\langle p_k^s \rangle$, that is $p_{\theta_1}^s \geq p_{\theta_2}^s \geq \ldots \geq p_{\theta_{|L|}}^s$. Then Θ also defines the same descending ordering for $\langle \gamma_k \rangle$, where $\gamma_k = p_k^s c^s - (1 - p_k^s) c^{ns}$ as in Eq. 2.*

Proof See [19]. □

Theorem 1 (Optimal mixture of arbitrary-size subsets in game C) *Let C be a zero-sum 'checking' game as described in Definition 1, with $0 \leq p_k^s \leq 1$, $\{c^s, c^{ns}\} \geq 0$, $L = \langle \ell_k \rangle \neq \emptyset$, $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} n_k$. Let $q_k \geq n_k$ be the upper limit (quota) for the size of the corresponding subset ℓ_k. Let Θ be the indices defining the descending ordering of $\langle p_k^s \rangle$, that is $p_{\theta_1}^s \geq p_{\theta_2}^s \geq \cdots \geq p_{\theta_{|L|}}^s$. Then the combined expectancy $v(C) = \sum_{k=1}^{|L|} v_k(C)$, regarding the partitioning into subsets $\ell_k \in L$ of corresponding sizes $n_k = |\ell_k|$, is maximized with:*

$$r : N_\Theta = \sum_{j=\theta_1}^{\theta r} q_j \leq N < \sum_{j=\theta_1}^{\theta_{r+1}} q_j \tag{5}$$

$$\langle n_k \rangle = \{q_{\theta_1}, \ldots, q_{\theta_r}, N - N_\Theta, 0, \ldots, 0\} \tag{6}$$

Proof See [19]. □

What Theorem 1 provides is a proof of the intuitive approach from everyday practice: when facing a set of $|L|$ choices associated with different rewards and a total sum N of selections, it is normal that the most logical thing to do is maximize the selections from the top rewards, then do the same for the second-best rewards, etc., until N is completed.

The same approach for the optimal strategy can be applied when the selections are of fixed subsets, which essentially makes the overall problem a discrete optimization task. Based on Theorems 1 and 2 proves that it reduces to selecting the subset of the best-reward options.

Theorem 2 (Optimal mixture of fixed-size subsets in game C) *Let C be a zero-sum 'checking' game as described in Definition 2 with $0 \leq p_k^s \leq 1$, $\{c^s, c^{ns}\} \geq 0$, $L = \langle \ell_k \rangle \neq \emptyset$, $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} n_k$. Let $n_k = q_k = |\ell_k|$ be the size and its upper limit (quota) for each subset $\ell_k \in L$, i.e., fixed for each $k \in \{1, \ldots, |L|\}$. Let $\gamma_k = p_k^s c^s - (1 - p_k^s) c^{ns}$ as in Lemma 1. Let Θ be the indices defining the descending ordering of $\langle n_k, \gamma_k \rangle$, that is $n_{\theta_1} \gamma_{\theta_1} \geq n_{\theta_2} \gamma_{\theta_2} \geq \ldots \geq n_{\theta_{|L|}} \gamma_{\theta_{|L|}}$. Then the combined expectancy $v(C) = \sum_{k=1}^{|L|} v_k(C)$, regarding the partitioning into subsets $\ell_k \in L$ of corresponding sizes $n_k = |\ell_k|$, is maximized with:*

$$r : N_\Theta = \sum_{j=\theta_1}^{\theta r} q_j \leq N < \sum_{j=\theta_1}^{\theta_{r+1}} q_j \tag{7}$$

$$\langle k \rangle \subseteq \Theta : \langle k \rangle = \{\theta_1, \ldots, \theta_r, \widehat{\theta_{r+1}}, 0, \ldots, 0\} \tag{8}$$

where $q_{\widehat{\theta_{r+1}}} = N - N_\Theta \leq q_{\theta_{r+1}}$.

Proof See [19]. □

Remark 1 For the last subset in position $\theta_{r+1} \in \Theta$ the value $n_{\theta_{r+1}} = N - N_\Theta$ may not be a valid option if it is not compatible with the fixed-size $\ell_{\theta_{r+1}}$ or, equivalently, the total sum may not be satisfied, i.e., $\sum_{k=1}^{|L|} n_k < N$. This depends on the exact partitioning L in relation to N and the defined quotas $\langle q_k \rangle$; this does not invalidate the general solution provided by Theorem 2.

It is worth noting that the descending ordering Θ in Theorem 2 is now strictly defined for $\langle n_k \gamma_k \rangle$ and cannot be deferred to $\langle p_k^s \rangle$ according to Lemma 1. This is because $n_k = q_k = |\ell_k|$ is now fixed and, thus, cannot be arbitrarily set to zero for the lower-ranked positions in $\langle n_k \rangle$. In that sense, Eq. 2 can be rewritten as:

$$v_k(C) = \delta_k q_k (p_k^s c^s - (1 - p_k^s) c^{ns}) \tag{9}$$

where $\delta_k \in \{0, 1\}\ \forall\, k \in \{1, \ldots, |L|\}$.

It should also be noted that the discrete case as stated in Definition 2 it is loosely related to the *subset sum* problem [25], which explores the different ways that a positive integer can be expressed as the sum of other positive integers. Another way to state the subset sum problem is: given a set of positive integers and a target sum N, does any subset of the numbers sum to precisely N; or more loosely, find a subset whose sum is as close as possible to N - this is precisely what Eq. 7 in Theorem 2 indicates regarding the selection of $\ell_k \in L$. However, the main difference here is that there is only one $|\ell_k|$ positive integer to use from each 'class' k in the sum, i.e., it is purely a matter of selection of singletons rather than combination of (possible) repetitions of numbers.

Based on Theorem 1, Algorithm 1 provides a baseline constructive procedure for calculating the optimal solution of Eqs. 5 and 6. Input $|L|$ defines compartments ℓ_k but not their sizes and inputs c^s, c^{ns} are not strictly necessary, they are only referenced for proper definition of the arg max equation. This algorithm also applies to the discrete case as described by Theorem 2, i.e., optimizing against $\langle k \rangle$ instead of $\langle n_k \rangle$, provided that: (a) the sorting statement for getting Θ is applied to $\langle n_k \gamma_k \rangle$; and (b) the last `if` statement also includes a validity check with regard to the value $N - N_\Theta$.

From Algorithm 1 it is obvious that the constructive procedure outlined is quite acceptable in terms of complexity. In fact, the most complex part is the sorting step, typically in the order of $O(n \log n)$. The iteration in the main loop is clearly linear at $O(n)$, since the two summations inside the loop are actually temporary variables stepwise-increased (no loops). This low-complexity property of the solution is particularly important for Theorem 2, showing that even though the discrete optimization task is combinatorial, the optimal solution can be constructed generally in $O(n \log n)$, or even $O(n)$ if the input vectors are already sorted.

Algorithm 1: Optimal mixture of partitioned pool

Result: Maximize the expected gain in mixing partitions of different success rates:

$$\langle n_k \rangle : \arg\max_{n_k} \sum_{k=1}^{|L|} n_k (p_k^s c^s - (1 - p_k^s) c^{ns}) \tag{10}$$

Input:
- partitioning: $L = \langle \ell_k \rangle \neq \emptyset, k = \{1, \ldots, |L|\}$
- constraint: $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} |\ell_k|$
- success rates: $\langle p_k^s \rangle = \{p_1^s, \ldots, p_{|L|}^s\},\ 0 \leq p_k^s \leq 1$
- subset quotas: $\langle q_k \rangle = \{q_1, \ldots, q_{|L|}\},\ |\ell_k| \leq q_k$
- marginal gain/cost: $\{c^s, c^{ns}\} \geq 0$

Output:
- subset sizes: $\langle n_k \rangle = \{n_1, \ldots, n_{|L|}\}$

sort $\langle p_k^s \rangle \rightarrow \Theta : p_{\theta_1}^s \geq p_{\theta_2}^s \geq \ldots \geq p_{\theta_{|L|}}^s$;
$\langle n_k \rangle \leftarrow \mathbf{0}$;
$r \leftarrow 0$;
$finished \leftarrow False$;
while $\neg finished$ **do**
  $r \leftarrow r + 1$;
  $n_{\theta_r} \leftarrow q_{\theta_r}$;
  $finished \leftarrow \left(\sum_{k=\theta_1}^{\theta_r} n_k \leq N \right) \wedge \left(\sum_{k=\theta_1}^{\theta_{r+1}} n_k > N \right)$;
end
if $\sum_{k=\theta_1}^{\theta_r} n_k < N$ **then**
  $n_{\theta_{r+1}} \leftarrow N - \sum_{k=\theta_1}^{\theta_r} n_k$;
end
return $\langle n_k \rangle$;

3.2 Evidence-Based Soft Partitioning

The game-theoretic formalization explored previously addresses a setup of 'compartmentalized' pool of N individuals according to some partitioning L, while having only one 'expert' with success rate p_k^s per subset $\ell_k \in L$. This essentially reduces the problem, in both continuous and discrete cases, to a convex optimization task as defined in Definitions 1 and 2, respectively. However, in the general case there may be no strict partitioning L and, hence, N may be one single pool of individuals - this is actually the generalization of having L defined by some *evidence* that updates the inclusion to some $\ell_k \in L$ and exclusion from the other $|L| - 1$ partitions of each individual, according to a posterior probability that is not strictly equal to unity. Additionally, there may be more than one 'experts' per such partition ℓ_k, each evaluating the individuals with a different success rate p_k^s and, hence, an aggregation scheme has to be applied for the final evaluation of 'safe' or 'non-safe' labelling. Equation 11 describes the Bayesian posterior probability of O_j of m mutually exclusive outcomes given an observed evidence E:

$$P(O_j|E) = \frac{P(E|O_j)P(O_j)}{\sum_{j=1}^{m} P(E|O_j)P(O_j)} = \frac{P(E|O_j)P(O_j)}{P(E)} \tag{11}$$

Exploiting evidence for posterior updates and combining aggregated experts is a highly challenging and multi-aspect research area that has been explored for many years from different disciplines, ranging from Evolutionary Biology and Sociology to Game Theory and Ensemble Learning [17, 23, 42]. In Sect. 4 the problem of optimal testing strategies for infectious diseases is restated in this general context, providing a proper analytical solution and proofs for combining multiple experts and with arbitrary posterior updates.

4 Weighted Majority Games

In collective decision-making, the individual outputs in an ensemble of experts with moderate performance levels are aggregated in order to produce a collective decision in an optimal way [18]. According to the Condorcet Jury Theorem [8], if the experts' individual decisions are independent and their corresponding estimations are more likely to be correct than incorrect ($p > 0.5$), then an increase in the collective performance of the ensemble is guaranteed when the individual estimations are combined with a plurality voting scheme. Moreover, this increase in performance continues to increase asymptotically as the size of the ensemble increases, i.e., as more independent experts are added.

Although the experts within such an ensemble can be viewed as competitive players each trying to impose its own choice upon the output of the ensemble, in reality this depends on the *coalitions* that each choice forms regarding these sub-groups. In other words, each expert is relevant to the collective output only if it participates in the sub-group that dictates this final decision, e.g., via majority voting. This cooperative type of games is well-studied within the context of Coalitional Gaming [31], a natural extension of the non-cooperative setups in classic Game Theory. In coalitional games, the optimality of the collective decision-making depends on the exact aggregation rule and the parameters or *weights* that are assigned to each member of the ensemble, typically in association to each competency level for the specific task at hand [17, 23].

The case of a having K options to choose from, using (weighted) plurality voting as aggregation rule, is defined as a Weighted Majority Game (WMG) [34]. It has been proven by Nitzan and Paroush [32] and Shapley and Grofman [38] that the optimal decision rules, in terms of collective performance, are the Weighted Majority Rules (WMR); this is in fact a different name for the well-known weighted majority voting schemes [26], which are often used in Machine Learning for combining hard-output classifiers. The same assertion has also been verified by Ben-Yashar and Nitzan [4] as the optimal aggregation rule for committees under the scope of informative voting in Decision Theory.

Within this context, Definition 3 and 4 formalize the Weighted Majority Voting (WMV) as the aggregation scheme for WMG, respectively. Furthermore, Definition 5 formalize the WMR as the optimal aggregation rule for such WMG setups.

Definition 3 (*Weighted Majority Voting (WMV)*) Let G be an ensemble of K decision-making 'experts' $\{D_1, \ldots, D_K\}$ with individual outputs $s_i \in \Omega$ against labels $\omega_j \in \Omega$ and corresponding accuracies $\{p_1, \ldots, p_K\}$. Then the voting *support* $g_j(\mathbf{x})$ for label ω_j given the input $\mathbf{x}$ is defined as:

$$g_j(\mathbf{x}) = \sum_{i \in K_j} w_i \ , \ K \supseteq K_j : \{s_i = \omega_j\} \tag{12}$$

where the *voting weights* w_i are typically defined as $0 \le w_i \le 1$ and $\sum_{i=1}^{K} w_i = 1$.

Definition 4 (*Weighted Majority Game (WMG)*) Let G be an ensemble of K decision-making 'experts' $\{D_1, \ldots, D_K\}$ in a WMV setup according to Definition 3. Then the Weighted Majority Game (WMG) of the ensemble defines the *winning coalitions* $K_{win} \subseteq K$ with regard to their corresponding output label as the ones having support $g_j(\mathbf{x})$ no less than a pre-defined lower threshold or decision *quota* q_{win}:

$$i \in K_{win} : g_j(\mathbf{x}) \ge q_{win} \ , \ K_{win} \subseteq K \tag{13}$$

Definition 5 (*Weighted Majority Rule (WMR)*) Let G be an ensemble of K decision-making 'experts' $\{D_1, \ldots, D_K\}$ in a WMG setup according to Definition 4, but with $q_{win} = 0$ and the largest support $g_j(\mathbf{x})$ always defining a single winning coalition. Then the Weighted Majority Rule (WMR) of the ensemble under these constraints is according to the output label with the maximum support $g_j(\mathbf{x})$:

$$i \in K \ : \arg\max_j g_j(\mathbf{x}) \tag{14}$$

In the case where there are $|\Omega|$ available choices for each expert, it is sufficient to define the decision threshold as $q_{win} = \frac{1}{|\Omega|}$ in order to ensure well-defined collective decisions in the sense of both Definitions 4 and 5, i.e., selecting the maximum-support option *and* satisfying the decision threshold at the same time.

4.1 Solution Concepts

As mentioned previously, WMR has been proven [4, 32, 38] as the theoretically optimal aggregation rule for WMG. This means that in any ensemble with K voting experts a set of voting weights $\langle w_i \rangle$ can be defined so that the corresponding WMR produces the optimal aggregation producing their collective decision. This is a particularly important result, since it only depends on the aggregation itself and not the design or the internal properties of each individual expert in the ensemble. Hence, the complexity of defining the optimal aggregation completely is reduced to the convex (see Definition 3) optimization task of defining vector $\langle w_i \rangle$, $i = \{1, \ldots, K\}$.

In the restricted case of having independent experts and (possibly) fractional weights $w_i \in \mathbb{R}$, the optimal design of WMR has been studied extensively and independently in a wide range of disciplines. Specifically, instead of the intuitive linear mapping of the experts' competencies $\langle p_i \rangle$ to corresponding voting weights $\langle w_i \rangle$ in WMV, the logarithm of the odds or *logodds* rule is applied. According to [22, 38], the logodds rule has been proposed for mixtures of experts as early as 1961 in [37]. In Machine Learning, the logodds rule re-appeared in the formulation of the Adaptive Boosting or 'Adaboost' algorithm [15] for robust ensemble meta-learning, which gave its creators Yoav Freund and Robert Schapire the 2003 Gödel Prize. In the last two decades the logodds method has used repeatedly in various meta-learning approaches as an analytical solution for optimal weighting in ensembles of experts, e.g. in classifier combination [23, 44], with proven performance over real-world problems and experimental datasets, very close and sometimes even higher than fully trained (non-analytical) weighting approaches [1, 16, 22].

Theorem 3 formally defines the logodds rule optimality for WMR weighting profiles, given conditionally independent decision-makers, and provides a short proof via Bayesian formulation. Next, Lemma 2 specializes it for the simple case of dichotomy choice situations.

Theorem 3 (Log-odds Optimality (general)) *Let G be an ensemble of K decision-making 'experts' $\{D_1, \ldots, D_K\}$ in a WMR setup according to Definition 5 and being conditionally independent, i.e., $P(s|\omega_j) = \prod_{i=1}^{K} P(s_i|\omega_j)$, $\omega_j \in \Omega$. Then the accuracy of the ensemble (P^w_{maj}) is maximized by assigning weights:*

$$w_i \propto \log \frac{p_i}{1 - p_i}$$

Proof See [19]. □

Lemma 2 (Log-odds Optimality (dichotomous choice)) *Let G be an ensemble of K decision-making 'experts' $\{D_1, \ldots, D_K\}$ in a WMR setup according to Definition 5 and being conditionally independent, i.e., $P(\boldsymbol{s}|\omega_j) = \prod_{i=1}^{K} P(s_i|\omega_j)$, with $s_i, \omega_j \in \Omega = \{-1, +1\}$. Then the accuracy of the ensemble (P^w_{maj}) is maximized by assigning weights:*

$$w_i = \log \frac{p_i}{1 - p_i}$$

and the optimal binary discriminator of the ensemble is:

$$g_{\pm}(\boldsymbol{x}) = (-\log P(\omega_-) + \log P(\omega_+)) + \sum_{i=1}^{K} s_i w_i \tag{15}$$

Proof See [19]. □

Taking into account the definition of $\langle w_i \rangle$ from Lemma 2 for the binary choice 'safe' or 'non-safe', target range $w'_i \in [0, 1]$ via Eq.?? and the convexity constraint $\sum_{i=1}^{K} \widehat{w}_i = 1$, Eq. 16 presents the final definition for the weighting profile $\langle \widehat{w} \rangle$ in WMR:

$$\langle \widehat{w} \rangle : \widehat{w}_i = {w'_i}/{\sum_{i=1}^{K} w'_i} = \frac{w_i - w_{min}}{w_{max} - w_{min}} / \sum_{i=1}^{K} \frac{w_i - w_{min}}{w_{max} - w_{min}} \tag{16}$$

What the WMG approach provides is a generalized approach to formulate the combination of K decision-makers, perhaps pooled into soft partitions by a Bayesian posterior update based on some membership evidence according to Eq. 11. The WMR is the theoretically optimal way to do this and the optimal combination weights for the decision-makers can be analytically defined based on their individual competencies according to Lemma 2 and Eq. 16. Given the fact that in the WMG approach the partitions are soft and not distinct as in Sect. 3, the game value is now defined across the entire set of N individuals and for all the decision-makers. Again, for the dichotomous choice of 'safe' or 'non-safe' individuals, this can be defined as:

$$v(G) = N \sum_{i=1}^{K} \left(p_i^s c^s - (1 - p_i^s) c^{ns} \right) \widehat{w}_i \tag{17}$$

where p_i^s is the competency of expert i on choice 'safe' and may be an updated Bayesian posterior according to Eq. 11.

4.2 Application to 'Checking' Games

Following the problem definition of Sect. 3, the optimization task here is how the entire set of N may be partitioned into $|L|$ subsets, where each expert may exhibit significantly increased competency and, hence, get a larger WMR weight that the others in the ensemble. In other words, instead of assigning each partition to a single expert as in Sect. 3, enable a combined decision according to WMG, but with Bayesian posterior updates that effectively introduce soft partitioning via the corresponding competency updates and, hence, the WMR weighting profile $langlew\rangle$.

For any such partition number $k \in \{1, \ldots, |L|\}$, Eq. 17 can be redefined as:

$$v_k(G) = n_k \sum_{i=1}^{K} \left(p_{i,k}^{s} c^{s} - (1 - p_{i,k}^{s}) c^{ns} \right) \widehat{w_{i,k}} \tag{18}$$

where $p_{i,k}^{s}$ is the competency of expert i in partition number k on choice 'safe', an updated Bayesian posterior according to Eq. 11 that effectively defines the soft partitioning into (non-distinct) subsets of sizes n_k with $\sum_{k=1}^{K} n_k = N$.

The difference of Eq. 18 with Eq. 2 is that the game value is estimated for each k of the partitions, employing $K > 1$ instead of only a single expert as in Sect. 3. Thus, for each partition number k, if only expert o ('oracle') is assigned with $\widehat{w_o} = 1$ and zero weight for every other expert in the ensemble, Eq. 18 reduces to Eq. 2.

Equation 18 can be explored in terms of optimality conditions against both competencies $\langle p_{i,k}^{s} \rangle$ and weights $\langle \widehat{w_{i,k}} \rangle$. The following Lemma 3 proves that the ordering of the competencies of the decision-makers also define the ordering of the expected payoffs for any partition.

Lemma 3 *Let G be a WMG 'checking' game of K decision-makers as described in Definition 4, with $0 \leq p_{i,k}^{s} \leq 1$, $iin\{1, \ldots, K\}$, $\{c^{s}, c^{ns}\} \geq 0$, $L = \langle \ell_k \rangle \neq \emptyset$, $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} n_k$. Let Θ_k be the indices defining the descending ordering of $\langle p_{i,k}^{s} \rangle$ for each k, that is $p_{\theta_{1,k}}^{s} \geq p_{\theta_{2,k}}^{s} \geq \ldots \geq p_{\theta_{K,k}}^{s}$. Then, if $p_{i,k}^{s} \geq \max\{\frac{c^{ns}}{c^{s}+c^{ns}}, 1/2\}$ and $\widehat{w_{i,k}}$ as defined in Eq. 16, Θ_k also defines the same descending ordering for $\langle \zeta_{i,k} \rangle$, where $\zeta_{i,k} = \left(p_{i,k}^{s} c^{s} - (1 - p_{i,k}^{s}) c^{ns} \right) \widehat{w_{i,k}}$.*

Proof See [19]. □

Lemma 3 is a generalization of Lemma 1 with the inclusion of WMR weighting. Based on this, Theorem 1 can now be reformulated accordingly for K decision-makers in an ensemble:

Theorem 4 (Optimal mixture of arbitrary-size subsets via WMG G) *Let G be a WMG 'checking' game of K decision-makers as described in Definition 4, with $0 \leq p_{i,k}^{s} \leq 1$, $i \in \{1, \ldots, K\}$, $\{c^{s}, c^{ns}\} \geq 0$, $L = \langle \ell_k \rangle \neq \emptyset$, $N = |\bigcup \ell_k| = \sum_{k=1}^{|L|} n_k$. Let $q_k \geq n_k$ be the upper limit (quota) for the size of the corresponding subset ℓ_k. Let Θ be the indices defining the descending ordering of $\langle \max_i p_{i,k}^{s} \rangle$ against k, that is $p_{\theta_1}^{s} \geq p_{\theta_2}^{s} \geq \ldots \geq p_{\theta_{|L|}}^{s}$, with $p_{i,k}^{s} \geq \max\{\frac{c^{ns}}{c^{s}+c^{ns}}, 1/2\}$. Then the combined expectancy $v(G) = \sum_{k=1}^{|L|} v_k(G)$, regarding the partitioning into subsets $\ell_k \in L$ of corresponding sizes $n_k = |\ell_k|$, is maximized with:*

$$r : N_\Theta = \sum_{j=\theta_1}^{\theta r} q_j \leq N < \sum_{j=\theta_1}^{\theta_{r+1}} q_j \tag{19}$$

$$\langle n_k \rangle = \{q_{\theta_1}, \ldots, q_{\theta_r}, N - N_\Theta, 0, \ldots, 0\} \tag{20}$$

Proof See [19]. □

What Theorem 4 states is that the logic of Theorem 1 is still valid for maximizing the overall payoff against a partitioned pool of N individuals to be tested. That is, even when an ensemble of K decision-makers is available for each partition, the subset sizes can still be maximized towards their corresponding quotas taking into account the maximum-position in the descending ordering of logodds-weighted marginal payoffs from the ensemble, instead of the single-expert assignment per partition. Of course, this approach is valid only when n_k is to be maximized against a single decision-maker that is to be selected as 'active' from the logodds-weighted ensemble. Instead, if all K decision-makers are considered 'active' in parallel and for every partition, then the generalized WMR in Definition 5 and the optimality proof from Theorem 3 are applied. In practice, this means that in Theorem 4 the descending ordering must be taken against the (generic) $\langle \zeta^s_{i,k} \rangle$ instead of replacing it with $\langle p^s_{i,k} \rangle$, i.e., optimizing each n_k in Eq. 18 for all $k \in \{1, \ldots, |L|\}$.

5 Sampling, Estimations and Posterior Updates

In the previous sections, the problem of optimizing the allocation of N individuals to be tested to K decision-makers was investigated under the assumption of distinct, soft or no partitioning of the pool, namely in Sect. 4 for the second (more generic) case and in Sect. 3 for the others. Based on the analysis above, it was proven that the optimal allocation for maximum payoff, i.e., maximum expectancy of selecting 'safe' individuals, depends on the ranking of the competency (or the logodds-weighted transformation of it) of the decision makers regarding this task. In other words, the performance of the members in the ensemble is the criterion upon which this optimal allocation is defined. Furthermore, this optimal allocation can be constructed analytically by employing Theorems 1, 2 or 4, according to the specific setup of the task with regard to the partitioning and the decision-makers.

Although the aforementioned approach is solid and constructive, it has a severe limitation in terms of actual real-world application. Namely, it assumes perfect knowledge of the decision makers' competencies, i.e., the corresponding vectors $\langle p^s_{i,k} \rangle$. This is rarely the case, since almost always the competencies are simply the best estimations we can get for the corresponding empirical success rates based on finite sample sets. In other words, each of the $p^s_{i,k}$ elements is an estimate, with a specific confidence interval and statistical significance value. Moreover, new sampling data should be incorporated in these estimations to provide a better result, i.e., a narrower and/or shifted confidence interval, in the sense of iteratively updating the corresponding posterior probabilities. Finally, the measurements upon the sample set may not be perfect, hence the estimation should also take into account this uncertainty. All these issues introduce factors of progressive complexity to the estimation of the competencies, not always easy to implement or even formulate as models.

5.1 Point Statistics and Confidence Intervals

The easiest option is to estimate the competencies $\langle p^s_{i,k} \rangle$ via standard sampling theory. From the problem definition and Table 1 in Sect. 2, it is established that the task at hand can be modelled as subsequent independent checks in a pool of 'safe' and 'non-safe' individuals, i.e., a series of Bernoulli trials. Hence, the proper probabilistic formulation of the corresponding random variable X of selecting 'safe' individuals ('hits') is via a Binomial distribution [40]:

$$f(x) = P(X = x) = \binom{n}{x} p^x q^{1-x} = \frac{n!}{x!(n-x)!} p^x q^{1-x} \tag{21}$$

where n is the number of trials, x is the number of 'hits', p is the competency for 'hits' and $q = 1 - p$ the complementary probability for the Bernoulli trials. According to these definitions, the mean value and standard deviation can also be defined as $\mu = np$ and $\sigma = \sqrt{npq}$, respectively.

The sampled values of mean μ and variance σ^2 are known to be *unbiased* estimators, i.e., they both converge to the actual values as the sample size increases. For the first this is true, for the second only approximately for large n:

$$E\left[\bar{X}\right] = \mu_{\bar{X}} = \mu \tag{22}$$

$$E\left[(\bar{X} - \mu)^2\right] = \sigma^2_{\bar{X}} = \left(\frac{N}{N-1}\right)\left(\frac{n-1}{n}\right)\frac{\sigma^2}{n} \approx \frac{\sigma^2}{n} \tag{23}$$

where the approximation in Eq. 23 is valid even when sampling $n \leq N$ without replacement from a population of size $N \to \infty$. In practice, the unbiased estimator of σ is usually defined according to:

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2 \Rightarrow E\left[S^2\right] = \mu_{S^2} = \frac{n-1}{n}\sigma^2 \tag{24}$$

$$\hat{S}^2 = \frac{n-1}{n}S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2 \Rightarrow E\left[\hat{S}^2\right] = \mu_{\hat{S}^2} = \sigma^2 \tag{25}$$

Hence, $\hat{S}$ is typically used instead of S as an unbiased estimator for small-sized samples. Based on these fundamentals from estimation theory, the confidence intervals of the (sample) mean value for any given confidence level $z_c > 0$ is given by:

$$\bar{X} - z_c \frac{\sigma}{\sqrt{n}} \sqrt{\frac{N-n}{N-1}} \leq \mu \leq \bar{X} + z_c \frac{\sigma}{\sqrt{n}} \sqrt{\frac{N-n}{N-1}} \tag{26}$$

for known σ and N, n as described above, i.e., the rightmost fractions are omitted for sampling with replacement or as $N \to \infty$. Similarly, if σ is unknown it is replaced by $\hat{S}$ or S and the same definition is given by:

$$\bar{X} - t_c \frac{\hat{S}}{\sqrt{n}} \leq \mu \leq \bar{X} + t_c \frac{\hat{S}}{\sqrt{n}} \tag{27}$$

The statistic z_c is defined according to the *Standard Normal* distribution given a specific significance level (two-tailed cummulative distribution function), e.g., for $\alpha = 0.05 \Rightarrow z_c = 1.960$. Similarly, t_c is defined according to the *Student's t* distribution given a specific significance level (two-tailed cumulative distribution function) and *degrees of freedom* (sample size), e.g., for $n = 20$, $\alpha = 0.05 \Rightarrow t_c = 2.093$. The t_c statistic provides a somewhat wider confidence interval due to the uncertainty of having a small sample size and/or unknown σ. Evidently, for $n > 30$ the confidence intervals provided by the two distributions are practically equal.

Using the previous formulation, the confidence intervals defined by Eqs. 26 and 27 can be specifically rewritten for the Bernoulli probabilities, i.e., the normalized estimations or *proportions* $\hat{p}$ and $\hat{q} = 1 - \hat{p}$ in Eq. 21. Specifically, setting $\hat{p} \propto \bar{X} = {}^{k}/_{n}$ with k 'safe' individuals detected in n tests, i.e., $\bar{X}$ is the relative frequency in the current sample, and since for Binomial distribution $\mu = np$ and $\sigma = \sqrt{npq} \approx \sqrt{\hat{S}^2} \to \sigma$, then:

$$\bar{X} - z_c \sqrt{\frac{p(1-p)}{n}} \sqrt{\frac{N-n}{N-1}} \leq \hat{p} \leq \bar{X} + z_c \sqrt{\frac{p(1-p)}{n}} \sqrt{\frac{N-n}{N-1}} \tag{28}$$

for known σ and N, n as described above, i.e., with the rightmost fractions omitted for sampling with replacement or as $N \to \infty$. Here, p is used for replacing $\sigma = \sqrt{p(1-p)}$, but in practice σ is also considered unknown (related to $\hat{p}$) and, thus, estimated via $\sigma \approx \hat{S}$ according to Eq. 25, while additionally using t_c instead of z_c statistic if the size of the sample is small ($n < 30$). A more accurate definition of Eq. 28 is [40]:

$$\hat{p} = \frac{\bar{X} + \frac{z_c^2}{2n} \pm z_c \sqrt{\frac{\bar{X}(1-\bar{X})}{n} + \frac{z_c^2}{4n^2}}}{1 + \frac{z_c^2}{n}} \tag{29}$$

where for large samples ($n > 30$) both Eqs. 28 and 29 are reduced to:

$$\hat{p} = \bar{X} \pm z_c \sqrt{\frac{\bar{X}(1-\bar{X})}{n}} \tag{30}$$

using the z_c statistic with the Standard Normal distribution or, more properly for unknown (estimated) $\sigma \approx \hat{S}$:

$$\hat{p} = \bar{X} \pm t_c \sqrt{\frac{\bar{X}(1-\bar{X})}{n}} \tag{31}$$

using the t_c statistic with the Student's t distribution.

Similar approaches can be employed for hypotheses testing regarding the prevalence level, i.e., accepting or rejecting a specific estimation $\hat{p} \approx \bar{X}$ based on z_c or t_c at a specific significance level α [39]. Specifically, the z_c statistic can be reformulated in a way that enables the significance testing of hypothesis H_0 that the sample-estimated $\bar{X}$ is 'close enough' to the assumed mean value μ (H_0 not rejected) at a significance level α, or reject it otherwise:

$$H_0 \ : \ -z_c \leq \frac{\bar{X}-\mu}{\sigma/\sqrt{n}} \leq z_c \tag{32}$$

where z_c is defined for a specific significance level, e.g., for $\alpha = 0.05 \Rightarrow z_c = 1.96$. Taking into account the properties of the Binomial distribution in Eq. 21 and, again, substituting for proportions $\bar{X} = \hat{p}, \mu = p, \sigma = \sqrt{p(1-p)}$, Eq. 32 can be rewritten as:

$$H_0 \ : \ -z_c \leq \frac{\hat{p}-p}{\sqrt{p(1-p)/n}} \leq z_c \tag{33}$$

which has the meaning of testing whether an estimated $\hat{p}$ is 'close enough' to the assumed prevalence p for the global population or if the specific sample (testing group) is α-significantly different. As previously described for the confidence intervals, proper adjustments can also be employed here for small-sized samples, using $\hat{S}$ instead of σ and t_c instead of z_c statistics.

5.2 Evidence-Based Posterior Updates

In Eq. 11 the simplest and most common form of the Bayes rule [40] is defined for m mutually exclusive outcomes O_j, using some evidence E to update their corresponding *posterior* probabilities. This is the most fundamental and generic way to express the fact that some *prior* probability is updated when new evidence becomes available, e.g., a supplementary or more recent testing sample, data related to another property of the associated subject, etc. Bayes approaches have been applied for many years as the basis for statistical modelling and empirical estimation of incidence rates [9, 20].

A more generic definition of Eq. 11 is when the underlying probability distribution is continuous, as it is in most cases. Let $\mathbf{x} = \{x_1, \ldots, x_n\}$ be a sample of some random variable X, $f(\mathbf{x})$ the corresponding probability density function that depends on some unknown parameter θ and Θ the random variable associated with that parameter θ having a probability distribution function $\pi(\theta)$. Then $f(x)$ may be described as the conditional density function of variable X given some $\Theta = \theta$, i.e., denoting it as $f(x|\theta)$ or 'x given θ'. Similarly, the joint probability of Θ given some $X = x$ is defined as $\pi(\theta|x)$. Then the joint probability of X and Θ can be defined as $f(x;\theta) = f(x|\theta)\pi(\theta)$. Moreover, given a sample $\mathbf{x}$ of X, the joint density function or *likelihood* can be written as $f(\mathbf{x}|\theta) = f(x_1|\theta) \cdot \ldots \cdot f(x_n|\theta)$ and the density function of θ given $\mathbf{x}$ as $\pi(\theta|\mathbf{x})$. With these definitions at hand, Eq. 11 can be rewritten in its more generic form as:

$$\pi(\theta|\mathbf{x}) = \frac{f(\mathbf{x};\theta)}{f(\mathbf{x})} = \frac{f(\mathbf{x}|\theta)\pi(\theta)}{\int_{\Theta} f(\mathbf{x}|\theta)\pi(\theta)d\theta} \tag{34}$$

where the integral is over the range of values for θ. In practice, calculating the integral over the entire range of θ is not necessary, since the denominator is independent of θ and the individual (exclusive) outcomes can be treated comparatively. This translates to redefining Eq. 34 in a simpler way as:

$$\pi(\theta|\mathbf{x}) \propto f(\mathbf{x}|\theta)\pi(\theta) \Leftrightarrow \pi(\theta|\mathbf{x}) = C \cdot f(\mathbf{x}|\theta)\pi(\theta) \tag{35}$$

where C is a proportionality constant independent of θ.

Based on this generic formulation of the Bayes rule, likelihood $f(\mathbf{x}|\theta)$ can be interpreted as the updated or posterior probability of observing samples $\mathbf{x}$ from random variable X given its conditioning parametrization by θ. Similarly, $\pi(\theta|\mathbf{x})$ can be interpreted as the probability density of parameter θ for X after observing samples $\mathbf{x}$. This later case is very interesting when θ is to be 'discovered' optimally from sample data in the sense of *maximum likelihood*. Although this task is similar to the approach presented earlier with the confidence intervals, Bayesian approaches are entirely different, since they always treat the corresponding target parameters as continuous probability distributions rather than spot statistics within some α-significance range of values [40, 41].

The difference between these two approaches, i.e., the classic confidence intervals versus the Bayesian methods, can be described more clearly for the case of estimating the proportion parameter p in the Binomial distribution of Eq. 21. In the more generic formulation, n is the number of trials and θ is the unknown parameter of the Binomial distribution of random variable X. Then θ has a Beta-related probability density function [40]:

$$\pi(\theta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{B(\alpha,\beta)}\ ,\ 0 < \theta < 1\ ,\ \{\alpha,\beta\} > 0 \tag{36}$$

where $B(\alpha,\beta)$ is the Beta function:

$$B(\alpha, \beta) = \int_0^1 u^{\alpha-1}(1-u)^{\beta-1} du \ , \ \{\alpha, \beta\} > 0 \tag{37}$$

If $\alpha = \beta = 1$ then $\pi(\theta)$ becomes the uniform density function on [0, 1], meaning that no assumption can be made for θ's distribution. Using Eq. 36 and the simplification of Eq. 35, the posterior density $\pi(\theta|x)$ given any observation x becomes:

$$\pi(\theta|x) \propto \frac{\theta^{x+\alpha-1}(1-\theta)^{n-x+\beta-1}}{B(x+\alpha, n-x+\beta)} \ , \ 0 < \theta < 1 \ , \ \{\alpha, \beta\} > 0 \tag{38}$$

which is actually similar to Eq. 36 but with parameters $x + \alpha$ and $n - x + \beta$. In words, if a random variable X is Binomial with parameters n and θ, with the prior density of θ being beta with parameters α and β, then the *posterior* density of θ after observing some $X = x$ is also beta with (updated) parameters α and β [40].

If more strict assumptions can be made for the prior density function of θ, two other common options are *Haldane's prior* with $\alpha = x$, $\beta = n - x$ in Eq. 37:

$$\pi(\theta) = \frac{1}{\theta(1-\theta)} \ \Rightarrow \ \pi(\theta|x) \propto \frac{\theta^{x-1}(1-\theta)^{n-x-1}}{B(x, n-x)} \ , \ 0 < \theta < 1 \tag{39}$$

and Jeffrey's prior with $\alpha = x + 1/2$, $\beta = n - x + 1/2$ in Eq. 37:

$$\pi(\theta) = \frac{1}{\sqrt{\theta(1-\theta)}} \ \Rightarrow \ \pi(\theta|x) \propto \frac{\theta^{x-1/2}(1-\theta)^{n-x-1/2}}{B(x+1/2, n-x+1/2)} \ , \ 0 < \theta < 1 \tag{40}$$

The definition in Eq. 38 is particularly useful in the context of the 'checking' game described in the previous sections. Specifically, it describes how the assumed prevalence p of the underlying Binomial distribution, associated to the probability p_k^s of selecting 'safe' individuals, is to be updated as new testing samples x become available. With confidence intervals this translated to increasing the sample size n and, thus, narrowing the limits of the α-significant range. Here, the Bayesian approach begins with little or no assumption ($\alpha = \beta = 1$) regarding the prior distribution of parameter $\theta = \hat{p}$ and after observing x the density function gets updated, with the posterior distribution being 'reshaped' more narrowly around the maximum likelihood 'best guess' of θ, while still remaining a continuous density function.

In order to see how the Bayesian approach exploits the evidence in $\mathbf{x}$ and improves the estimation of θ, the Binomial distribution of can be treated via Normal distribution approximation as described earlier, in order to make the analysis of X posteriors more tractable. In particular, for a random sample of size n for X drawn from a Normal distribution with unknown mean value θ ($\bar{X}$ in the sample) and known variance σ^2, as well as a prior distribution of θ that is Normal with mean value μ and variance v^2, it can be proven [40] that the posterior distribution for θ is also Normal with mean value μ_{post} and variance v_{post}^2 given by:

$$E[\theta]_{post} \approx \mu_{post} = \frac{\sigma^2\mu + nv^2\bar{X}}{\sigma^2 + nv^2} \tag{41}$$

$$Var[\theta]_{post} \approx v^2_{post} = \frac{\sigma^2 v^2}{\sigma^2 + nv^2} \tag{42}$$

In words, Eq. 41 defines how μ prior for the mean value of θ is updated after observing $\bar{X}$ in the current sample of size n, provided that the corresponding variances σ^2 and v^2 are both known. Similarly, Eq. 42 defines how v^2 prior for the variance of θ is updated based on that same sample. For better understanding, the comparison of prior versus posterior for the variance can be made in terms of the reciprocal of it, thus defining the *precision*:

$$\xi_{prior} = \frac{1}{v^2} \Rightarrow \xi_{post} = \frac{1}{v^2_{post}} = \frac{1}{v^2} + \frac{n}{\sigma^2} = \xi_{prior} + \xi_{data} \tag{43}$$

where the second term in ξ_{post} can be considered as the precision of the observed data, denoted by ξ_{data}. It is clear that according to Eq. 43, the smaller the variance of a distribution, the larger is its precision value. Then Eqs. 41 and 42 can be rewritten as:

$$E[\theta]_{post} \approx \mu_{post} = \frac{\xi_{prior}\mu + \xi_{data}\bar{X}}{\xi_{prior} + \xi_{data}} \tag{44}$$

$$Var[\theta]_{post} \approx \frac{1}{\xi_{post}} = \frac{1}{\xi_{prior} + \xi_{data}} \tag{45}$$

What Eqs. 44 and 44 describe under the Bayesian scope is fundamental: As the sample size increases, so does the precision of the (posterior) variance, while the estimated mean value gets weighted more and more towards the sample (data) mean instead of the its prior. In words, *the larger the sample size, the better estimates the posteriors provide for the mean and variance over their corresponding priors*. Not surprisingly, this is similar to what happens with the range of their confidence intervals for spot value estimations, as noted earlier. However, the Bayesian context provides a more intuitive way of viewing this effect on parameter θ as transitioning from a state of little information (wide prior distribution) to more specific information (narrower posterior distribution).

Besides confidence interval estimation, the Bayesian framework also enables the analytical calculation of conditional distributions for future observations based on a currently available observed sample. Although the approach is similar, the difference is that instead of the overall posterior density function, the probability of a specific outcome is now estimated, hence the name Bayesian *predictive distributions* for this family of methods. As an example, based on Eq. 38 for a beta distribution for a random variable X, the joint probability of observing $Y = y$ after obtaining a posterior for θ can be defined as [40]:

$$f(y,\theta|x) = f(y|\theta)\pi(\theta|x) = \binom{m}{y} \frac{\theta^{x+y+\alpha-1}(1-\theta)^{m+n-x-y+\beta-1}}{B(x+\alpha, n-x+\beta)} \tag{46}$$

where $0 < \theta < 1$, $\{\alpha, \beta\} > 0$, $y = \{0, \ldots, m\}$ and $\{n, m\}$ the sizes of the first (observed) and the second (future) sample sizes. Then, the predictive probability function for Y is the marginal density obtained by integrating Eq. 46 over θ:

$$f^*(y) = \int_0^1 \binom{m}{y} \frac{\theta^{x+y+\alpha-1}(1-\theta)^{m+n-x-y+\beta-1}}{B(x+\alpha, n-x+\beta)} d\theta \tag{47}$$

$$= \binom{m}{y} \frac{B(x+y+\alpha, m+n-x-y+\beta)}{B(x+\alpha, n-x+\beta)} \tag{48}$$

What Eq. 48 provides is the point probability of observing y in a future sample of size m, based on the posterior update as previously defined for θ. In a way, it is much like hypothesis testing of whether the future sample's distribution parameter θ is consistent with its estimation on the currently available sample, but with the Bayesian approach it is, again, a (predictive) distribution function rather than an accept/reject outcome.

6 Further Complications in Real-World Testing

The description thus far in the previous sections was focused on three main aspects:

- Game-theoretic optimal strategies for ensuring risk mitigation.
- Optimal estimation of the critical probabilistic parameters.
- Optimal posterior updates for safety margin assurances.

For the game-theoretic strategies, only the general setup of the testing process is necessary to define the optimal way to plan the risk-mitigation testing for infectious diseases, given that the goal is to maximize the pool of 'safe' (or, equivalently, minimize the pool of 'non-safe') individuals and provided that the capability of the (one or more) decision-makers in selecting those from the general pool can be accurately estimated. For this estimation, samples can be used for confidence intervals or Bayesian methods, while subsequent observations can also be exploited via posterior updates.

The issue that is prevalent in real-world testing and not covered by the aforementioned framework is related to the evidence used, i.e., the observed samples. Normally in statistics the observations are considered with absolute certainty, counting different outcomes or properties in a pool of samples without any possibility of measurement error or lack of information. However, in reality these measurements are also subject of probabilistic functions that dictate their reliability and the certainty of the outcome. If this certainty is adequately close to 100% it is usually ignored as a factor, but the typical estimation models can not address situations where this is not a valid assumption. Instead, the evidence itself must be estimated via confidence intervals or Bayesian methods, before it can be used as observation to subsequent estimation procedures.

In testing for infectious diseases this situation is a very common case-specific factor that needs to be taken into account. Neither of the two main categories of tests, molecular or antigen 'rapid', exhibit perfect sensitivity or specificity and, hence, their diagnostic accuracy is close but certainly lower than 100%. There are several ways to assess the accuracy of these medical testing procedures and, hence, the certainty of the evidence which they provide in statistical terms. More commonly, *sensitivity* and *specificity* represent the two major factors in any empirical (data-driven) assessment related to the confidence on the evidence regarding positive and negative hypotheses, respectively. In addition, medical testing can also be characterized by the positive and negative *predictive value*, which are related to the confidence on the evidence regarding positive and negative test outcomes, respectively.

Regarding SARS-CoV-2, Table 2 presents the corresponding numbers for five commercially available antigen 'rapid' tests (2020), for different levels of sampled-estimated prevalence [29]. It is clear that testing outcomes can not be assumed to exhibit perfect certainty, hence the statistical evidence on 'safe' or 'non-safe' individuals is strong but not absolute. This means that every priors estimation and posterior updates should take this into account, leading to much more complex probabilistic treatment than what was presented in the previous sections.

What Machine Learning provides is a data-driven view of these estimation tasks and an abstraction level 'above' the underlying statistical complications that are unknown or too complex to express analytically [23, 42]. At the same time, the theoretical foundations from Artificial Intelligence and, more precisely, the structural risk minimization of models that are trained with empirical evidence (datasets) ensure that the final estimations are optimal w.r.t. some core criterion, which is normally the maximum likelihood estimation for the 'true' parameters of these 'unknown' probabilistic models [41]. Two such typical examples are Support Vector Machines (SVM) [42], which can be designed specifically to maximize the discrimination margin between predicted classes or, equivalently, to minimize the structural risk of the empirical error of the trained model, i.e., generalized from a limited training dataset to the global problem; and Bayesian Networks [41], which naturally incorporate the notion of imperfect information (uncertainty) and cascaded propagation of evidence-based probabilistic estimation of outcomes from node to node as a continuous flow.

One specific factor that caught the attention of researchers during after the initial surge of the SARS-CoV-2 pandemic and the emergence of readily available 'rapid' test kits was the option of having lower accuracy but massive tests in the general population [30]. Low accuracy in testing translates to low sensitivity and/or specificity, which in turn produces low positive and/or negative predictive value. After observing the evolution of the national epidemic in several countries, especially after lifting the international travel bans during the summer of 2020, researchers have argued that in practice these policies may work much better than expected. Although this seems counter-intuitive in statistical terms, 'rough' but massive screening in the population can be a decisive pre-emptive contingency measure against the spreading of the

Table 2 Indicative performance of antigen 'rapid' SARS-CoV-2 tests from five different companies (2020), for different levels of sampled-estimated prevalence $\bar{X}$, based on $n = 1000$ sample patients. [29]

$\bar{X} = 0.02$	STY (%)	SPY (%)	TP	FP	FN	TN	PPV (%)	NPV (%)
Comp. 1	100.00	94.29	20	56	0	924	26.32	100.00
Comp. 2	95.00	98.47	**19**	15	1	965	**55.88**	99.90
Comp. 3	100.00	93.06	20	68	0	912	22.73	100.00
Comp. 4	90.00	97.24	18	27	2	953	40.00	99.79
Comp. 5	85.00	97.24	17	27	3	953	38.64	99.69
$\bar{X} = 0.30$	STY (%)	SPY (%)	TP	FP	FN	TN	$PPV(\%)$	$NPV(\%)$
Comp. 1	100.00	94.29	300	40	0	660	88.24	100.00
Comp. 2	96,67	98.57	**290**	10	10	690	**96.67**	98.57
Comp. 3	98.67	93.14	296	48	4	652	86.05	99.39
Comp. 4	89.67	93.14	269	48	31	652	84.86	95.46
Comp. 5	85.33	97.14	256	20	44	680	92.75	93.92

virus. Having many false positives means putting into quarantine more individuals than necessary, but this can be considered as acceptable cost during such a global emergency. Having many false negatives means missing some individuals, but the massive scale of tests overcomes this drawback by detecting much more 'non-safe' individuals in total. In words, both cases of low-performance testing may lead to better overall mitigation strategies and contingency policies against a pandemic such as SARS-CoV-2.

7 Conclusions

In this study, the general problem of developing optimal testing strategies for infectious diseases like SARS-CoV-2 was explored under the scope of Game Theory, sampling and estimation methods from classic Statistics, as well as Bayesian methods for the proper treatment of posterior updates. Overall, it is a very challenging research topic that requires deep understanding and somewhat new point of view, combining multiple aspects of crowd dynamics, risk management and Machine Learning, which are usually employed individually by researchers depending on their main field of expertise.

Six main guidelines have been established by this work:

1. The core task of any such screening process via testing in transit hubs and gateways is minimizing the risk of introducing infectious individuals in the

general population; there is no point in maximizing the 'hit rate' of the tests, especially when the testing pool is very limited.

2. Risk minimization is inherently associated with (estimated) variance minimization of incidence rates for each sampling group; hence, allocating testing resources according to this principle must be the core screening policy.
3. When planning an inflow-allocation strategy for a specific capacity from multiple groups, risk minimization dictates that maximizing quotas towards lower-ranked incidence groups is the optimal policy.
4. Multiple decision-making independent 'experts' (models) for detecting 'safe' versus 'non-safe' individuals can be combined optimally via analytical solutions from Coalitional Games, specifically Weighted Majority Voting.
5. Estimated confidence intervals must be used instead of point means for proper control of risk margins; even more, Bayesian methods provide a more intuitive way for continuous posterior updates exploiting testing results.
6. In order to cope with the increased complexity of uncertainty in evidence (test reliability), Machine Learning methods are appropriate for data-driven maximum likelihood estimation of parameters and structural risk minimization.

It is imperative to stress out the differences between common cost/benefit optimization methods like bandit algorithms from Operational Research and the risk-minimization target of the problem treated here: *maximizing the detection value of any single test does not minimize the posterior incidence risk for the population*. If tests themselves are put in the center of the optimization goal, there is no guarantee whatsoever that the risk of infection propagation is minimized. In other words, *minimum infection risk, not optimal resource allocation, is the real challenge and top priority*.

Under the scope of these core principles described above, any screening policy designed by the decision-making authorities is guaranteed to minimize the risk of introducing infectious individuals to the general population.

References

1. Ahsen, M., Vogel, R., Stolovitzky, G.: Unsupervised evaluation and weighted aggregation of ranked classification predictions. J. Mach. Learn. Res. **20**(166), 1–40 (2019)
2. Augenblick, N., Kolstad, J., Obermeyer, Z., Wang, A.: Group testing in a pandemic: the role of frequent testing, correlated risk, and machine learning. Natl. Bure. Econ. Res. (2020)
3. Bairagi, A., Masud, M., Kim, D., et.al.: A noncooperative game analysis for controlling covid-19 outbreak. pp. 1739–1776 (2020)
4. Ben-Yashar, R., Nitzan, S.: The optimal decision rule for fixed-size committees in dichotomous choice situations: the general result. Int. Econ. Rev. **38**, 175–186 (1997)
5. Besbes, O., Gur, Y., Zeevi, A.: Stochastic multi-armed-bandit problem with nonstationary rewards. Adv. Neural Inf. Process. Syst. pp. 199–207 (2014)
6. Boeing: Covid-19 screening strategy comparisons (2021)
7. Caparros, A., Finus, M.: The corona-pandemic: a game-theoretic perspective on regional and global governance. Environ. Res. Econ. 1–15 (2020)

8. de, m.: Condorcet. In: An Essay on the Application of Probability Theory to Plurality Decision Making: An Election Between Three Candidates. University of Oxford, UK (1989)
9. Devine, O., Louis, T., Halloran, E.: Empirical bayes methods for stabilizing incidence rates before mapping. Epidemiology 622–630 (1994)
10. Dong, E., Du, H., Gardner, L.: An interactive web-based dashboard to track covid-19 in real time. Lancet Infect. Dis. (2020)
11. Centers for Disease Control and Prevention (CDC): Overview of testing for sars-cov-2 (covid-19) (2021)
12. Centers for Disease Control and Prevention (CDC): Testing strategies for sars-cov-2 (2021)
13. European Centre for Disease Prevention and Control (ECDC): Covid-19 testing strategies and objectives (2020)
14. European Centre for Disease Prevention and Control (ECDC).: Testing strategies for sars-cov-2 (2021)
15. Freund, Y., Schapire, R.: A short introduction to boosting (in japanese). J. Jpn Soc. Artif. Intell. **14**(5), 771–780 (1999)
16. Georgiou, H., Mavroforakis, M., Theodoridis, S.: A game-theoretic approach to weighted majority voting for combining svm classifiers. In: Kollias, S., Stafylopatis, A., Duch, W., Oja, E. (eds.) Artificial Neural Networks–ICANN 2006, pp. 284–292. Berlin, Heidelberg (2006)
17. Georgiou, H.: Collective decision efficiency and optimal voting mechanisms: a comprehensive overview for multi-classifier model, pp. 1–21 (2015). arXiv:1502.02191
18. H Georgiou. Games People Play—Conflicts, Mechanisms and Collective Decision-making in Expert Committees, 1st edn. (2015) (e-book). Arxiv:1506.0168
19. Georgiou, H.: A game-theoretic and statistical approach to designing optimal testing strategies for infectious diseases (to appear) (2021)
20. Greenland, S., Robins, J.: Empirical-bayes adjustments for multiple comparisons are sometimes useful. Epidemiology 244–251 (1991)
21. Kasy, M., Teytelboym, A.: Adaptive targeted infectious disease testing. Oxford Rev. Econ. Policy **36**, s77–s93 (2020)
22. Kuncheva, L.: Fuzzy versus nonfuzzy in combining classifiers designed by boosting. IEEE Trans. Fuzzy Syst. **11**(6), 729–741 (2003)
23. Kuncheva, L.: Combining Pattern Classifiers: Methods and Algorithms. Wiley-Interscience, USA (2004)
24. Lauer, S., Grantz, K., Bi, Q., Jones, F., et.al.: The incubation period of coronavirus disease 2019 (covid-19) from publicly reported confirmed cases: Estimation and application. Ann. Internal Med. (2020)
25. Lipschutz, S., Lipson, M.: Discrete Mathematics, 3rd edn. McGraw-Hill (2009)
26. Littlestone, N., Warmuth, M.K.: The weighted majority algorithm. Inf. Comput. **108**, 212–261 (1994)
27. Luo, H., Wei, C.-Y., Agrwal, A., Langford, J.: Efficient contextual bandits in nonstationary worlds. In: Conference Learning Theory, pp. 1739–1776 (2018)
28. Lyng, G., Sheils, N., Kennedy, C., et al.: Identifying optimal covid-19 testing strategies for schools and businesses: Balancing testing frequency, individual test technology, and cost. PLoS ONE **16**(3), e0248783 (2021)
29. McWilliams, C., Kamran, K., Procop, G.: Testing 1-2-3: Testing strategies for employers in the era of covid-19 (2020)
30. Mina, M., Parker, R., Larremore, D.: Rethinking covid-19 test sensitivity—a strategy for containment. N. Engl. J. Med. **383**(22), e120(1–3) (2020)
31. Montet, C., Serra, D.: Game Theory and Economics. Palgrave Macmillan (2003)
32. Nitzan, S., Paroush, J.: Optimal decision rules in uncertain dichotomous choice situations. Int. Econ. Rev. **23**, 289–297 (1982)
33. Norizuki, M., Hachiya, M., Motohashi, A., et al.: Effective screening strategies for detection of asymptomatic covid-19 travelers at airport quarantine stations: exploratory findings in Japan. Global Health Med. **3**(2), 107–111 (2021)
34. Owen, G.: Game Theory, 3rd edn. Academic Press, USA (1995)

35. Ozkaya, M., Izgi, B.: Effects of the quarantine on the individuals' risk of covid-19 infection: Game theoretical approach. Alex. Eng. J. **60**(4), 4157–4165 (2021)
36. Paltiel, D., Zheng, A., Walensky, R.: Covid-19 screening strategies that permit the safe re-opening of college campuses, pp. 1–36 (2020)
37. Pierce, W.: Improving reliability of digital systems by redundancy and adaptation. Ph.D. dissertation, Stanford Univ., USA (1961)
38. Shapley, L., Grofman, B.: Optimizing group judgemental accuracy in the presence of independence. Public Choice **43**, 329–343 (1984)
39. Spiegel, M.R., Liu, J., Lipschutz, S.: Mathematical Handbook of Formulas and Tables, 4th edn. McGraw-Hill (2012)
40. Spiegel, M.R., Schiller, J., Srinivasan, R.A.: Probability and Statistics, 3rd edn. McGraw-Hill (2009)
41. Theodoridis, S.: Machine Learning: A Bayesian and Optimization Perspective, 2nd edn. Academic (2020)
42. Theodoridis, S., Koutroumbas, K.: Pattern Recognition, 4th edn. Academic (2008)
43. World Health Organization (WHO): Recommendations for national sars-cov-2 testing strategies and diagnostic capacities—interim guidance (2021)
44. Yuksel, S., Wilson, J., Gader, P.: Twenty years of mixture of experts. IEEE Trans. Neural Netw. **23**(8), 1177–1192 (2012)

Contact Tracing for Healthcare Facilities Using Bluetooth

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Abstract Bluetooth is seen as a key technology for contact tracing and exposure notification applications, with the goal of monitoring and containing outbreaks of the COVID-19 pandemic. However, the use of contact tracing apps has been limited among the population as the technology still faces fundamental limits in terms of proximity accuracy, resources, and privacy. Still, the potential benefits are evident for scenarios such as critical healthcare facilities, where most vulnerable people are present. The aim of this chapter is to present an architecture with heterogeneous devices that support contact tracing and exposure notification in hospitals and nursing homes, while meeting the required level of accuracy and privacy. The framework is based on standard Bluetooth mesh networking technology, and it accounts for realistic propagation conditions. The impact of configuration parameters and channel conditions is analyzed, along with proposals for research and standardization directions.

Keywords Bluetooth · Mesh · Contact tracing

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1 Introduction

COVID-19 is a high transmissible disease (before and immediately after symptom onset) also suggesting that finding and isolating symptomatic patients alone may not suffice to contain the epidemic. According to this, a recent study [1] analyzed the impact of contact tracing in Belgium, estimating a potential average reduction in hospital admissions of 57% with contact tracing services in place, assuming that 70% of the symptomatic cases are subject to contact tracing and comply with home isolation. In this context, digital contact tracing is proven to be extremely efficient to reduce the delay of intervention and to automate the tracing procedure compared to human-based contact tracing. Since the start of the COVID-19 pandemic, the research community has worked intensively on the definition of reliable and secure apps for digital contact tracing. Apple and Google built an opt-in and decentralized way of allowing individuals to know if they have come into close contact with COVID-19 confirmed cases [2]. Apps developed for this purpose allow a device to scan for other devices in the background, storing data locally. If tested positive, the user may authorize the data to be provided to the health authorities, who can then trace others who happened to be in proximity. The benefits of the use of contact tracing apps on a smartphone rely on the assumption that the majority of the population installs and uses the app regularly [3, 4]. As of June 2021, the adoption and use of Governmental contact tracing apps among the population is unfortunately relatively low (i.e., around 15% of population).The slow penetration rate of the technology is not only due to the privacy but also due to fundamental limitations of the accuracy of proximity detection. However, during the first wave of COVID-19 pandemic, the Italian National Institute of Health (ISS) reported that more than 40% of analyzed COVID-19 cases in Italy were linked to nursing homes and 10% of cases have been related to outbreaks in hospitals. While extensive vaccination campaigns help prevent the severe symptoms and the coronavirus disease, the containment of the spread of the pandemic is not guaranteed with vaccination only. Therefore, the prevention and control of this and future outbreaks can greatly benefit from the protection of critical facilities through a targeted, efficient contact tracing solution. In these scenarios, Bluetooth mesh networking [5] offers a low cost, flexible, standard infrastructure that can be deployed to enable contact tracing, but it is compatible with additional profiles and applications in use in the hospital (lighting, heating, and ventilation control), without the need of deploying an ad-hoc infrastructure of devices that only works for the purpose of the current pandemic.

In this chapter, we focus on the potential and the limitations of currently available digital contact tracing solutions based on Bluetooth. As a major contribution, we present a comprehensive framework for supporting contact tracing services for critical healthcare facilities. The envisioned infrastructure relies on a hierarchical architecture and the use of standardized protocols for collecting proximity data instead of a typical peer-to-peer fashion using smartphone apps. The core idea and a preliminary evaluation was published in [6]. In this study, we consider recent literature advancements, and we take into consideration new discoveries in the past year regarding digital contact tracing. Furthermore, we explore an extended experimental evaluation that includes also the joint impact of configurable application parameters, such as the RSSI threshold, environmental conditions such as the duration of an exposure, and network conditions in terms of advertising packet loss probability, on the correct exposure notification probability in a densely deployed scenario.

The chapter is structured as follows. Section 2 introduces the digital contact tracing scenario. In Sect. 3, we provide an overview of the Bluetooth technology. We review the technical challenges associated to the existing contact tracing framework in Sect. 4, and describe the proposed approach in Sect. 5. Extensive simulation results are discussed in Sect. 5.1. Finally, we summarize our conclusions and future work in Sect. 6.

2 Digital Contact Tracing

Contact tracing, along with vaccination, robust testing, isolation, and care of cases, is a key strategy for interrupting chains of transmission of the coronavirus and reducing mortality associated to COVID-19. Traditional contact tracing is practiced by the Departments of prevention through interviewing cases and contacts made by phone or with home visits and other ways to be able to identify all the contacts of a case, depending on the context of exposure, test laboratory, contact monitoring to verify the possible onset of symptoms and application of quarantine and isolation measures. Digital contact tracing makes extensive use of technological solutions for digital health, with the effect of drastically reducing the personal contacts between public health professionals and the population at risk.

The contact tracing scenario defined in this study aims at complying with the guidelines from WHO, in particular when referring to healthcare environments [7]. There are strict protocols in most of the hospitals and health care facilities for isolation of patients that are tested positive to COVID-19 in restricted areas. However, a critical scenario for contact tracing and exposure notification is in the non-COVID areas and gray areas, where patients that are not considered at risk later happen to be tested positive. In this sense, a contact is a person who has had any one of the following exposures to a probable or confirmed case:

- face-to-face contact with a probable or confirmed case within 1 m and for at least 15 min;
- direct physical contact with a probable or confirmed case;
- direct care for a patient with probable or confirmed COVID-19 disease without the use of recommended PPE; or
- other situations as indicated by local risk assessments.

A person that is tested positive to COVID-19 must inform the public health authority about all contacts from 2 days before and 10 days after symptom onset (or positive test if asymptomatic). There are different risks associated to a contact depending on the context where the potential exposure happens, whether people are vaccinated, and they use personal protective equipment (PPE). Any patient hospitalized in the same room or sharing the same bathroom as a COVID-19 patient, visitors to the patient, or other patient in the same room or other rooms visited by the COVID-19 patient (e.g., common dining facilities) is listed as a potential person at risk. It is evident that the requirements are much stricter than in the general case for contact tracing, as it is not sufficient to perform only seldom measurements in a time frame of 15 min, as current exposure notification services do [2], but many critical interactions that depend on location (people in the same room) need to be captured by the digital contact tracing solution more frequently.

3 The Bluetooth Technology

An overview of the Bluetooth technology is provided in this section, starting from the Bluetooth Low Energy specification [8] and then focusing on the Mesh networking specification [5].

3.1 Bluetooth Low Energy

The primary use case for Bluetooth has been for a long time the wireless connection between a headphone and a headset. Bluetooth Low Energy was released in 2010 as a part of the Bluetooth 4 Core specifications, with the objective to extend the Bluetooth ecosystem towards Internet of Things applications. Bluetooth supports connection-oriented and connection-less data transfer modes. In connection-oriented mode, devices negotiate dedicated channel and schedules for data transmission. In the connection-less mode, denoted as advertising mode, short messages (i.e., advertising packets, or beacon messages) are broadcast over random access channels. Connection-less mode supports quick estimation of the position and proximity of a device, using the received signal strength indicator (RSSI) of the received advertising packets. Each advertising packet consists of a short header, followed by a small payload, containing an identifier of the transmitting device plus a short message (typically up to 31 bytes). This advertising payload is used to indicate that the packet is associated with a particular service or app, e.g., a contact tracing app.

As a recent advancement of the Bluetooth Low Energy technology, the release of Bluetooth 5.1 Core specification in 2019 defined improved localization services. Combined with extended advertising capabilities and improved data transfer modes, there has been a boost in the adoption and deployment of Bluetooth beacons and location-based services [9, 10]. The increased data rates, in addition to the rather obvious benefits of increased throughput and reduced latency, decreases the time on air to save battery consumption and improve coexistence with other technologies that operate in the same band and often coexist within the same device (e.g., Wi-Fi) [11–13].

The Bluetooth security architecture includes five distinct features: pairing, bonding, device authentication, encryption, and message integrity: it is designed to provide protection against passive eavesdropping and protection against man-in-the-middle attacks. The standardized full stack architecture guarantees strong protection at the device level, although there is no user authentication [14]. Furthermore, Bluetooth provides privacy by supporting a feature that reduces the ability to track a device over a period of time by changing the Bluetooth device address on a frequent basis.

3.2 Bluetooth Mesh Profile

Bluetooth mesh introduced networking specification on top of the Bluetooth technology to take additional market shares in the Internet of Things (IoT) connectivity space. Formally, Bluetooth mesh is defined as a *profile*, that can run on top of any device compatible with Bluetooth Low Energy. Bluetooth profiles define the required functions and features of each layer in the Bluetooth stack, from the physical layer to the application. A profile defines the vertical interactions between the layers, as well as the peer-to-peer interactions of specific layers between devices forming a mesh network.

The design of Bluetooth mesh profile aims at creating a simple, efficient, and flexible wireless mesh networking protocol solution. The Bluetooth mesh profile standardizes a layered protocol architecture, as illustrated in Fig. 1. Each layer has its own functions and responsibilities, and provides services to the layer above. The access to the radio is handled by the Bluetooth core technology, with advertising data format defined by the bearer layer. The network and transport layers are functional to the network design and strategies for deployment. The network layer handles aspects such as addressing and relaying of messages, as well as encryption and authentication within the network. The lower transport layer handles segmentation

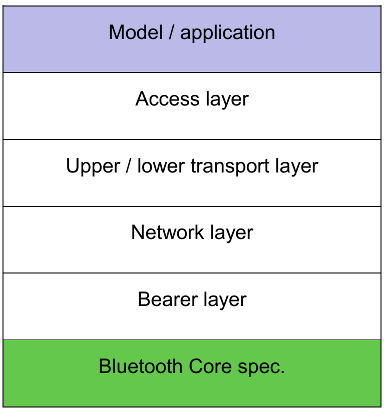

Fig. 1 Bluetooth mesh layered architecture

and reassembly, and provides acknowledged or unacknowledged transport of data end-to-end. The upper transport layer encrypts and authenticates access messages, and defines transport control mechanisms, including the management of low power nodes. The access layer is responsible for application-to-network traffic management and end-to-end data transfer. An application interacts with the protocol stack via standardized models, which define message format and configuration of the application parameters [5].

With the introduction of Bluetooth mesh, potentially thousands of nodes can interact with each other without establishing a connection. After provisioning the devices in the network, there is no need for centralized algorithms, nor coordination and, most importantly, there is no single point of failure in the network. A group of nodes can be addressed with a single command, so that dissemination and collection of information is efficient and reliable.

Currently, Bluetooth mesh is supported at a smartphone only through proxy connections via a dedicated node of the network, which is called Proxy and takes responsibility of injecting and collecting traffic in the network from and towards the smartphone. Determining the correct number of proxies in a network, the number of relays, and efficient solutions for interference mitigation is a challenging task that is under discussion in the research community and standardization bodies. The performance of Bluetooth Mesh has been evaluated through simulations in [15, 16] and through a set of experimental campaigns in [17].

4 Key Challenges

There are major concerns about the feasibility of reliable and robust contact tracing solutions based on the Bluetooth technology. The main challenges are classified into four categories, namely, estimation accuracy, device resources, privacy, and technology penetration rate.

4.1 Estimation Accuracy

Distance estimation is the baseline paradigm for digital contact tracing. Typically, this is based on measurements taken by a Bluetooth receiver involving the signal strength of incoming advertising packets. The variability of wireless channel behavior is not particularly severe for line-of-sight short range distance estimation, however, the attenuation level of the signal may deviate even if the distance is constant due to many environmental factors. Multipath propagation has a strong influence, especially in closed environments with reflecting objects and surfaces. To overcome this, averaging over frequent measurements is a solution in most cases. Other inconveniences may arise from propagation without direct or clear electromagnetic visibility. As an example, a smartphone device in a pocket, with human body obstructing direct visibility may experience higher attenuation with respect to a smartphone device carried in hand; the smartphone itself may be protected by a more or less robust cover that can also be built using non-plastic materials. Furthermore, a Bluetooth chip can be employed by devices with different kind of materials: as an example, aluminum frames may determine a larger electromagnetic attenuation than plastic materials. Moreover, barrier protections and PPEs drastically reduce the risk of contagion, but their impact on distance estimation measurements is not easy to account for.

For single-hop broadcasting, Bluetooth Core supports the so-called *proximity profile* [8], which defines the behavior when a device moves away from a peer device so that the connection is dropped or the path loss increases above a predefined level, causing an alert. The proximity profile can also be used to define the behavior when the two devices come closer together, but a connection is required to perform the RSSI measurements associated to the profile. This is not sufficient to cover the use case proposed in this paper.

In [18], the authors show the results of an experimental study to validate the impact of various factors such as distance, orientation, obstacles, and time of the day on the Bluetooth RSSI measurements, showing that a limited number of RSSI measurements is not sufficient for the purpose of accurate distance estimation. The authors of [19] study the impact of channels, distances, and user's orientation in the positioning phase on the accuracy of Bluetooth positioning. The accuracy obtained is within 1.5 m and the precision is 90% within the range of 1.5–2.5 m.

Radio frequency fingerprinting in support of RSSI measurements has been proposed in [20] as a means to enhance positioning accuracy of Bluetooth. Mackey et al. [21] analyzes the performance of Bluetooth beacons in terms of their accuracy in proximity estimation. Three Bayesian filtering techniques to improve the estimation accuracy of BLE beacons are analyzed. With this approach, the achieved proximity error is 0.27 m at a distance of 3 m, using 1000 RSSI measurements.

In [22], indoor localization measurements are conducted using Bluetooth mesh device implementations. The study concludes that a careful design of the network and interference management is important, as it affects the positioning accuracy of existing algorithms. Similarly, an automated indoor localization system that relies on low-cost Bluetooth localization with low data acquisition and network configuration overhead is proposed in [23]. The proposed system incorporates a sophisticated visual-inertial localization algorithm for a fully automated collection of Bluetooth signal strength data. While several machine learning techniques have been proposed to improve the proximity accuracy, most recent works still show the fundamental boundaries of proximity estimation of devices off-the-shelf [6, 24, 25].

Recently, infield measurements in [26] have shown that a basic linear and logarithmic model for the analysis of signal path loss of Bluetooth can provide sufficient estimation accuracy for exposure notification in different scenarios. Furthermore, exposure detection can be improved if knowledge about the user position with respect to the device can be inferred.

4.2 Device Resources

A device with Bluetooth connectivity enabled typically advertises the services it supports roughly every 100 ms with little impact on the resources (i.e., battery, computation capabilities) [8]. Therefore, transmitting short advertising packets periodically to enable a contact tracing application should not be a problem even for a resource constrained device. However, the main problem when performing distance estimation measurements is that a device needs to keep its Bluetooth receiver continuously on for sufficiently long time to collect unsolicited advertising packets from other devices. This is critical for the battery consumption, as a Bluetooth receiver consumes approximately 15 mA of current when it is turned on. If continuously active during 24 h, it can impact the available capacity of a typical 3000 mAh battery in a smartphone for about 12% [6].

Methods to optimize the scanning cycle of Bluetooth devices have been proposed in the literature (e.g., [27]), but this is not always possible in the case of battery powered devices such as smartphones since radio resources are shared among the various active services, including active Bluetooth connections, and even the use of Wi-Fi connectivity impacts the availability of the Bluetooth receiver [9].

For these reasons, apps running in the background on a smartphone are typically allowed to scan for incoming Bluetooth advertising packets only for a few seconds every 5 min [2]. Therefore, when compared to devices that have duty cycle close to 100% (e.g., relay nodes in a Bluetooth mesh), a smartphone may take more than 10 times to collect the same number of RSSI measurements for use in distance estimation and contact tracing.

4.3 Privacy and Security

Contact tracing services handle critical data such as medical condition and potentially position of a user at any time. The user needs to trust the Central Authority and the owner of the contact tracing service for preserving the privacy of the information, as the system can be in theory always misused for mass surveillance or unclear scopes, beyond the original purpose of pandemic containment. Indeed, a relevant problem for some contact tracing apps available for our smartphones is third-party information sharing [28]. Several contact tracing apps analyzed by [28] mention outsourcing data to third parties, and it is not clear what data is shared to whom and how it is processed by these parties.

Both centralized and decentralized approaches have been proposed for privacy preserving contact tracing. The recent Google/Apple solution implements a decentralized approach, where each device protects its identity by using random temporary exposure keys, and encrypted identifiers that are frequently refreshed [2]. Theoretically, nobody except the user can easily understand if two temporary codes have been transmitted by the same device, not even the central authority. Each user connects periodically to the server and receives the entire list of infected users. At that point, the user's device can securely check if this list contains one of the previously observed random identifiers and notify the user if at risk.

Although governmental contact tracing apps are designed to provide a certain level of privacy, there can be intentional or unintentional risks for users, since also apps designed with care to this aspect imply that positive users reveal all the codes transmitted to the server during the vulnerability period [29]. This potentially allows the server, or a malicious attacker, to make the person identifiable. Centralized approaches for data storage suffer more from denial of service attacks. To overcome this limitation, distributed approaches for preserving privacy are investigated in the research community. Blockchain is currently evaluated as a method for data logging and retrieval (e.g., as described in [30]), but the impact in terms of cost and computation for these solutions is high in consideration of the scale of the application [31].

Compared to general Bluetooth Low Energy, where security feature are optional, and it is allowed to have a device with no security protections or constraints is use, Bluetooth mesh has mandatory security features [5]. The network, individual applications and devices are all secure and this cannot be switched off or limited. In the Bluetooth mesh security, there are various types of security keys. Between them, these keys provide security to different aspects of the mesh and achieve a critical capability in mesh security, that of *separation of concerns*. The network may be subdivided into subnets and each subnet has its own network key, which is possessed only by those nodes which are members of that subnet. This might be used, for example, to isolate specific, physical areas, such as each rooms in a facility. Application data for a specific application can only be decrypted by nodes which possess the right application key. Across the nodes in a mesh network, there may be many distinct application keys, but typically, each key is possessed by a small subset of the nodes, namely those of a type which can participate in a given application. Therefore, the inherent security solution of Bluetooth mesh can provide a strong substrate for the security in the digital contact tracing application.

4.4 Technology Adoption

The technology adoption is a critical factor, since a contact tracing service requires that the majority (60%) of the monitored population must have the app downloaded and active [3]. The Bluetooth technology has a great potential, as it is available in all modern smartphones and there is a large ecosystem of compatible devices. 95% of people in South Korea owns a modern smartphone. However, in Europe and US, this percentage varies from 60 to 80% of the population and the number reduces drastically below 40% in developing countries. India has been hit severely by coronavirus and the smartphone penetration is at 25.3% [32], smartphone app-based approach will not be sufficient. Low-cost wristband-based proximity detection solutions could be used in low-socioeconomic areas with the cooperation of community health workers.

Despite a high percentage of smartphone adoption in developed countries, there is some skepticism around the potential success of contact tracing solutions among the public, whenever it is not enforced, and it is only partially attributable to the technical limitations discussed above. Indeed, the adoption and use of Governmental contact tracing apps among the population is surprisingly low across the world (i.e., typically below 15% of population). This fact encourages a more focused effort and targeted use of the technology in key areas, where the containment of the pandemic is critical, and the use of the technology can be enforced.

5 Contact Tracing Architecture

In this section, we describe the system architecture and deployment guidelines for building a Bluetooth mesh standards-based infrastructure to support the contact tracing services for critical healthcare facilities.

The main elements of the proposed system architecture for digital contact tracing are illustrated in Fig. 2. We define four different roles of devices in the architecture, depending on functionality and resource capabilities, namely the *beaconing tag*, the *proximity detector*, the *mesh relay*, and the *gateway*.

The beaconing tag is a relatively simple device that should work for years without having to be recharged or having a battery replaced. Besides the model associated to the contact tracing apps, it only implements the underlying Bluetooth Core implementation, with no need to implement states and behaviors associated to the mesh profile stack. In healthcare facilities, the use of beaconing tags can be enforced to all doctors and patients. The beaconing tags are programmed to transmit a short advertising message every 250 ms. The frequency is in line with current recommendation for notification exposure [2].

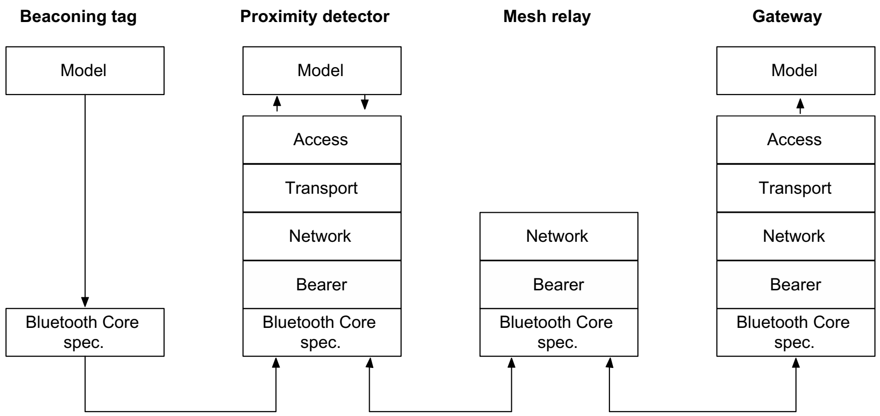

Fig. 2 System architecture for the proposed Bluetooth mesh infrastructure for contact tracing

The proximity detector is the device that is configured to monitor and send messages based on the presence, absence, or movement of the beaconing tag. Contrary to the beaconing tag, proximity detector needs to have resources to scan the advertising channels periodically and perform mesh procedures, thus implementing the full stack, including the model associated to the contact tracing app. However, the states and behaviors associated to the Bluetooth mesh relay feature are not mandatory in the proximity detector. Proximity detectors and the Gateway may be smartphones and existing Bluetooth mesh-capable devices deployed within the facility. Each proximity detector continually reports back to the proximity engine all tags it can hear above a predefined RSSI threshold, as well as the RSSI measurement from each.

A relay node forwards messages received from other nodes over the advertising channels. The relay node is the equivalent role of a generic relay in the Bluetooth mesh networking protocol. Therefore, the relay node is provided with the network security keys associated to the mesh network, but it does not need to implement the higher layers of the Bluetooth mesh protocol stack and does not need to be provided with the security credentials associated to the contact tracing application to participate in the message collection. Mesh relays can be Bluetooth mesh relay capable devices deployed within the facilities, with no software upgrade needed.

Finally, the gateway node is a generic mesh node that provides an interface with the contact tracing server, where the advanced computation of the proximity data is performed, and relevant data is stored. The gateway must be provided with an implementation of the model associated to the contact tracing apps and must support application-programming interfaces through a communication infrastructure with the proximity engine at the contact tracing server. The proximity engine uses RSSI information, as well as the known position of each proximity detector, to estimate the position of tags based on trilateration.

An example of deployment scenario on a reference topology is illustrated in Fig. 3. The main advantage of implementing this architecture in healthcare facilities such as nursing homes and hospitals, compared to general purpose scenario, is that the use of devices such as beaconing tags and proximity detectors can be imposed to personnel and patients, and potentially to registered visitors, via internal regulation or by the local authority, so that the adoption of the technology is enforced.

Privacy aspects and their implication are easier to handle in restricted scenarios for contact tracing in healthcare facilities compared to other scenarios, since access and presence of staff and patients is already monitored and visitors may need to register to access the premises. Different risk profiles can be attributed to people, based on role, performed activity, diligence, and expertise in usage of PPEs, vaccination status, and previous clinical conditions.

To improve accuracy and robustness to the presence of obstacles, patients, and users may be provided with instructions on how to properly carry the tag. As an example, a tag carried as a visible necklace (or a wristband) preserve high correlation between electromagnetic visibility and face-to-face contact, which is a situation at risk.

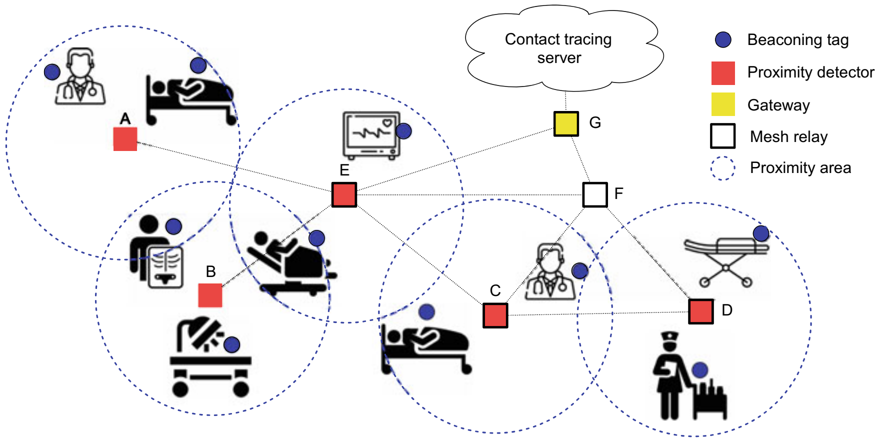

Fig. 3 Bluetooth mesh infrastructure with example topology. Beacons are identified with small colored circles. Nodes A and B are simple proximity detectors, as they can read and process messages from beacons in their surrounding proximity area, which is limited by the dotted circles. Nodes C, D, and E behave as proximity detectors with respect to surrounding beacons, but also implement the relay feature of Bluetooth mesh to forward data received by proximity detectors and other mesh nodes in the network. Nodes F and G only serve as relay nodes and gateway, respectively, carrying traffic toward the contact tracing engine, but do not perform proximity detection

5.1 Performance Results and Discussions

We conducted extensive measurement campaigns using nRF Connect for mobile app [33], running on two iOS smartphones, one acting as a beaconing tag, and one acting as a proximity detector, placed at various distances. The advertising interval was set to 250 ms and the total scanning period was set from 15 to 60 min. A preliminary experimental campaign with this setup was reported in [6]. Here, to reproduce a scenario with multiple access interference given by the presence of multiple beaconing tags and proximity detectors in the same network, we considered various levels of additional advertising packet loss probability artificially added at the receiver, and ranging from 0 to 30%. The performance of the network was evaluated in terms of exposure notification probability, i.e., the probability that the proximity detector receives advertising packets determining RSSI measurements above a predetermined RSSI threshold for a period of 15 min within the observation period. The exposure notification probability was obtained analyzing the RSSI trace at nRF Connect, and missed RSSI measurements were not considered in the computation.

In Fig. 4, we report the probability of exposure notification by varying the observation period from 15 to 60 min. The probability is reported for various values of the threshold in the interval from −57 dBm to −66 dBm, for a distance between the beaconing tag and the proximity detector of 1 m in Fig. 4a and 2 m in Fig. 4b. Basically, the exposure notification probability for a given threshold measures the

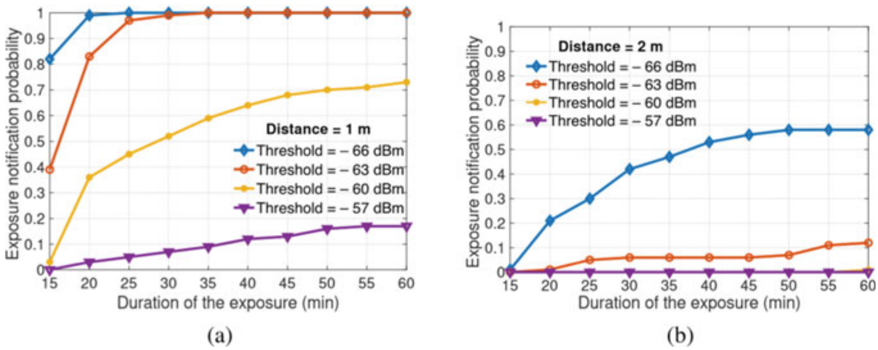

Fig. 4 Probability of exposure notification vs. duration of the exposure at a proximity detector for a beaconing tag at the distance of **a** 1 m and **b** 2 m

probability of correct notification of an exposure (true positive), whereas its complement to one measures the probability of missing the notification of exposure for a beaconing tag that is in proximity (false negative). Similarly, by looking at Fig. 4b, we can retrieve the probability of notification of exposure triggered by a beaconing tag that is actually not in proximity (false positive) and its complement to one that measures the probability that the exposure is not notified (true negative).

The probability of a false detection of proximity, which triggers an exposure notification for a device that has not been actually in close contact, needs to be low to avoid that a person is put in isolation and tested based on inaccurate information. However, it is more critical to have a device that has been in close contact that does not exhibit long-term average RSSI capable of triggering an exposure notification (false negative), as this is more dangerous for the purpose of monitoring and containing the spread of the pandemics.

The range of thresholds presented in Fig. 4 considers only values that are significant for the contact tracing scenario. Indeed, an RSSI threshold lower than −66 dBm gives a significant probability that a device that is farther than 2 m is detected as an exposure, whereas on the contrary a threshold above −57 dBm gives a very low probability of correct exposure notification.

As a result observable in Fig. 4, the best performance in terms of exposure notification probability for devices that are actually in proximity is obtained for the lowest RSSI threshold of −66 dBm. However, a device that is at 2 m is incorrectly notified with probability above 20% after 20 min of exposure, and the probability increases to above 50% for longer exposures. Instead, an RSSI threshold at −63 dBm provides a probability of correct notification of an exposure above 95% for an exposure of 25 min, and a probability of false notification of an exposure below 5% for the same duration of the exposure, representing a reasonably good trade off that could be used as a default value set by the Bluetooth model.

A high sensitivity of the results with respect to the threshold is also observed in Fig. 4. This corresponds to a high sensitivity to inaccurate RSSI estimation and scenario-dependent bias on the attenuation. As an example, a 3 dB constant bias in the measurement of the received power at 1-m distance may increase the probability of false negative within 30 min exposure from 2 to 48%. Therefore, it is fundamental that the threshold can be changed by the configuration manager based on the knowledge of the deployment area. Walls can affect proximity measurements by 6–12 dB. However, such additional path loss is not negative for proximity measurements, as close contacts with a wall in between should not be counted.

While a higher sampling rate in transmission and a long scanning period in reception may provide high proximity accuracy, they considerably increase the cost of in terms of energy consumption. Hence, there is a clear fundamental tradeoff between proximity accuracy and device resources depending on the sampling rate and scanning cycles. One of the main advantages of the proposed asymmetric architecture with a combination of beaconing tags and a network of more proximity detectors is that it can balance proximity accuracy and battery lifetime of constrained devices. Repeated measurements within an interval give high accuracy in the detection of close contacts. If the transmission interval is 250 ms and a smartphone can scan for 30 s every 5 min, the proximity detection can be based on 360 RSSI measurements. A mesh node, such as a monitor, can scan the advertising channels with 100% duty cycle, except when the device is occupied in re-transmitting messages. Therefore, there are potentially 3600 measurements available at a proximity detector in 15 min if scanning continuously.

The number of proximity detectors needs to be sufficient to detect beaconing tags at any location within a few meters of distance, to perform accurate distance estimation. Therefore, in an indoor healthcare facility, depending on the geometry of the map, the recommended density of proximity detector is one node every 10 m^2. The number of relay nodes may be much lower, as it is sufficient that every node can be reached via Bluetooth advertising. Therefore, depending on the geometry of the map, the recommended density of proximity detector is one node every 50 m^2.

To further validate the analysis in a general mesh scenario with multiple access interference added by the presence of multiple beaconing tags, we included an additional advertising loss probability that is applied to the RSSI trace obtained with the experimental campaign. In Fig. 5, we report the probability of exposure notification for a duration of the exposure of 20, 25 and 30 min and distance 1 m, for increasing advertising loss probability up to 30%.

As it can be seen in Fig. 5a for a duration of the exposure that is lower than 20 min, the impact of multiple access interference becomes relevant as the probability of loss is above 20%. For a threshold of −63 dBm, the probability of correct notification of exposure drops from 70 to 10% when increasing the additional advertising packet loss probability from 20 to 30%. This is due to the difficulty to even obtain a sufficient number of measures to correctly detect a 15 min exposures. However, as the duration of the exposure increases above 25 min in Fig. 5b, the effect is less pronounced, and the exposure notification probability becomes rather insensitive to the advertising packet loss probability for the reference threshold at −63 dBm as the duration of the exposure is at least 30 min in Fig. 5c.

In general, we can say that we tested very severe conditions for the additional packet loss probability, in particular in the context of Bluetooth mesh networks. In

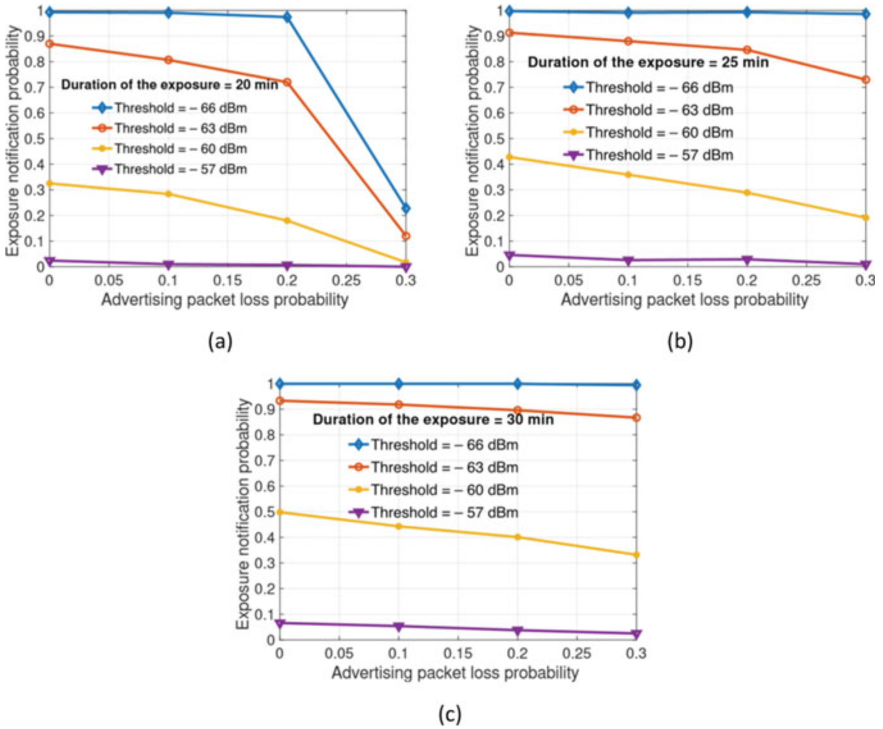

Fig. 5 Probability of exposure notification versus advertising loss probability at a proximity detector for a distance of 1 m and 20 min of exposure

fact, although the broadcasting nature of Bluetooth mesh may suggest that multiple access interference is an issue for the reliability of the advertising data transfer, especially in a large-scale scenario, this is not entirely correct for a properly configured mesh network, as experimentally validated for a 879 devices building automation scenario in [16], with more than 99% of successful data transfers. This is due to the short duration of mesh advertising packet transmissions (around 300us) and the use of channel and spatial redundancy [8]. Indeed, with an advertising interval of 250 ms, the channel occupation for a beaconing tag is about 0.12%.

6 Conclusions and Prospected Directions

The Bluetooth technology has a key role in digital contact tracing applications, leveraging a large ecosystem of compatible devices and localization-based services. The effectiveness of digital contact tracing in large scale scenarios such as hospitals and nursing homes is potentially high, but limitations and concerns emerged about technology adoption, estimation accuracy, efficient use of device resources, and privacy of existing solutions. However, critical facilities can benefit from the deployment of simple, flexible, cost-effective, local infrastructures to support contact tracing, especially if based on a standardized networking solution. We proposed and evaluated a system architecture for contact tracing based on the Bluetooth mesh standard, addressing challenges and opportunities for its adoption in critical facilities. We showed through experiments the sensitivity of the exposure notification service to the RSSI threshold, multiple access interference and duration of the exposure, showing that the configuration of parameters such as the RSSI threshold is the most critical component. Moving forward from the approach followed by the Google/Apple solution, we believe that the RSSI threshold and the advertising interval should be configuration parameters that are set by the configuration manager.

The framework proposed in this paper can provide relevant use case requirements for specifying a suitable model that covers application in proximity detection and contact tracing in critical facilities. In particular, the concept that introduces the role of proximity detector that is separated from the beaconing tag role can be standardized, with the possibility to separate the security domains between the beaconing tag and the proximity detector, and the proximity detector and the rest of the mesh. The great advantage of exploiting a standardized solution is that the facility manager will not be forced to deploy a full-size infrastructure dedicated only to contact tracing and proximity detection, but it can reuse existing Bluetooth devices already deployed in the infrastructure as proximity monitors and can deploy Bluetooth mesh devices such as luminaries and sensors that can be used for other purposes beyond the contact tracing needs, which will be hopefully not necessary for long time. Applications would even be able to perform different risk assessments for different pathology, without being forced to rely on a "black-box" framework, specifically designed for only one type of risk, whose parameters can not be set by applications built on top of it. Furthermore, a deeper understanding of the mechanisms of contagion might involve updates in the definition of exposure to risk and, in the future, profiles may be updated considering different mechanisms of contagion, eventually not only related to some safety distance and exposure time.

References

1. Willem, L., Abrams, S., Libin, P.J.K., Coletti, P., Kuylen, E., Petrof, O., Møgelmose, S., Wambua, J., Herzog, S.A., Faes, C., Beutels, P., Hens, N.: The impact of contact tracing and household bubbles on deconfinement strategies for covid-19. Nat. Commun. **12**(1), 1524 (2021). [https://doi.org/10.1038/s41467-021-21747-7
2. *E*xposure notification - Bluetooth specification, Apple and Google, September 2020. https://www.blog.google/documents/62
3. Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D., Fraser, C.: Quantifying sars-cov-2 transmission suggests epidemic control with digital contact tracing. Science **368**(6491) (2020)
4. Hernández-Orallo, E., Manzoni, P., Calafate, C.T., Cano, J.: Evaluating how smartphone contact tracing technology can reduce the spread of infectious diseases: the case of covid-19. IEEE Access **8**, 99 083–99 097 (2020)

5. Bluetooth Mesh Profile Specifications 1.0.1., Bluetooth SIG (2017). https://www.bluetooth.com/specifications/mesh-specifications
6. Di Marco, P., Park, P., Pratesi, M., Santucci, F.: A bluetooth-based architecture for contact tracing in healthcare facilities. J.Sensor Actuator Netw. **10**(1) (2021). https://www.mdpi.com/2224-2708/10/1/2
7. Contact tracing in the context of COVID-19 (Interim Guidance), World Health Organization (WHO), February 2021. https://www.who.int/emergencies/diseases/novel-coronavirus-2019
8. Bluetooth Core Specification 5.2, Bluetooth SIG (2019). https://www.bluetooth.com/specifications/bluetooth-core-specification
9. Di Marco, P., Skillermark, P., Larmo, A., Arvidson, P., Chirikov, R.: Performance evaluation of the data transfer modes in bluetooth 5. IEEE Commun. Stand. Magaz. **1**(2), 92–97 (2017)
10. Pau, G., Arena, F., Gebremariam, Y.E., You, I.: Bluetooth 5.1: An analysis of direction finding capability for high-precision location services. Sensors **21**(11) (2021). https://www.mdpi.com/1424-8220/21/11/3589
11. Collotta, M., Pau, G., Talty, T., Tonguz, O.K.: Bluetooth 5: a concrete step forward toward the IoT. IEEE Commun. Mag. **56**(7), 125–131 (2018)
12. Di Marco, P., Chirikov, R., Amin, P., Militano, F.: Coverage analysis of bluetooth low energy and IEEE 802.11ah for office scenario. In: 2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), pp. 2283–2287 (2015)
13. Del Carpio, L.F., Di Marco, P., Skillermark, P., Chirikov, R., Lagergren, K., Amin, P.: Comparison of 802.11ah and ble for a home automation use case. In: 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), pp. 1–6 (2016)
14. Lonzetta, A., Cope, P., Campbell, J., Mohd, B., Hayajneh, T.: Security vulnerabilities in bluetooth technology as used in IoT. J. Sens. Actuator Netw. **7**(3), 28 (2018). July
15. Rondon, R., Mahmood, A., Grimaldi, S., Gidlund, M.: Understanding the performance of bluetooth mesh: reliability, delay, and scalability analysis. IEEE Internet Things J. **7**(3), 2089–2101 (2020)
16. Di Marco, P., Skillermark, P., Larmo, A., Arvidson, P.: Bluetooth mesh networking. Ericsson White Paper, vol. 284 23–3310 Uen (2017)
17. Hernández-Solana, A., Pérez-Díaz-De-Cerio, D., García-Lozano, M., Bardají, A.V., Valenzuela, J.: Bluetooth mesh analysis, issues, and challenges. IEEE Access **8**, 53 784– 53 800 (2020)
18. Gu, Y., Ren, F.: Energy-efficient indoor localization of smart hand-held devices using bluetooth. IEEE Access **3**, 1450–1461 (2015)
19. De Blasio, G., Quesada-Arencibia, A., García, C.R., Rodríguez-Rodríguez, J.C., MorenoDíaz, R.: A protocol-channel-based indoor positioning performance study for bluetooth low energy. IEEE Access **6**, 33 440–33 450 (2018)
20. Ng, P.C., She, J., Ran, R.: A compressive sensing approach to detect the proximity between smartphones and ble beacons. IEEE Internet Things J. **6**(4), 7162–7174 (2019)
21. Mackey, A., Spachos, P., Song, L., Plataniotis, K.N.: Improving ble beacon proximity estimation accuracy through bayesian filtering. IEEE Internet Things J. **7**(4), 3160–3169 (2020)
22. Jürgens, M., Meis, D., Möllers, D., Nolte, F., Stork, E., Vossen, G., Werner, C., Winkelmann, H.: Bluetooth mesh networks for indoor localization. In: 2019 20th IEEE International Conference on Mobile Data Management (MDM), pp. 397–402 (2019)
23. Tomažič, S., Škrjanc, I.: An automated indoor localization system for online bluetooth signal strength modeling using visual-inertial slam. Sensors **21**(8) (2021). https://www.mdpi.com/1424-8220/21/8/2857
24. Leith, D., Farrell, S.: Coronavirus contact tracing: evaluating the potential of using bluetooth received signal strength for proximity detection. Preprint, May (2020). https://arxiv.org/abs/2006.06822
25. Hatke, G.F., Montanari, M., Appadwedula, S., Wentz, M., Meklenburg, J., Ivers, L., Watson, J., Fiore, P.: Using bluetooth low energy (ble) signal strength estimation to facilitate contact tracing for covid-19 (2020)

26. Etzlinger, B., Nußbaummüller, B., Peterseil, P., Hummel, K.A.: Distance estimation for ble-based contact tracing—a measurement study. Wireless Days (WD) **2021**, 1–5 (2021)
27. Song, S.W., Lee, Y.S., Imdad, F., Niaz, M.T., Kim, H.S.: Efficient advertiser discovery in bluetooth low energy devices. Energies **12**(9), 1707 (2019). May
28. Azad, M.A., Arshad, J., Akmal, S.M.A., Riaz, F., Abdullah, S., Imran, M., Ahmad, F.: A first look at privacy analysis of covid-19 contact tracing mobile applications. IEEE Internet of Things J. Early Access, 1–1 (2020)
29. Krehling, L., Essex, A.: A security and privacy scoring system for contact tracing apps. J. Cybersecur. Privacy **1**(4), 597–614 (2021). https://www.mdpi.com/2624-800X/1/4/30
30. Garg, L., Chukwu, E., Nasser, N., Chakraborty, C., Garg, G.: Anonymity preserving iotbased covid-19 and other infectious disease contact tracing model. IEEE Access **8**, 159 402–159 414 (2020)
31. Chowdhury, M.J.M., Ferdous, M.S., Biswas, K., Chowdhury, N., Muthukkumarasamy, V.: Covid-19 contact tracing: challenges and future directions. IEEE Access **8**, 225 703–225 729 (2020)
32. Turner, A.: How Many Smartphones are in the world (2020). http://CNN.com
33. nRF Connect for mobile, Nordic Semiconductor. https://www.nordicsemi.com/Software-and tools/Development-Tools/nRF-Connect-for-mobile

Non-invasive COVID-19 Detection and Diagnostic Systems

Monitoring the Health and Movement of Quarantined COVID-19 Patients with Wearable Devices

Muhammad Nazrul Islam, Nafiz Imtiaz Khan, Noor Nafiz Islam, Samuli Laato, and A. K. M. Najmul Islam

Abstract This study explores the requirements and possibilities of wearable devices for ensuring and supporting the home quarantine of suspected COVID-19 patients. We adopted a design science research (DSR) approach and conducted a requirement elicitation study through semi-structured interviews with 36 participants including doctors, home quarantined people and local administrative personnel. Based on the analysis of the interview data, we identified some design considerations for the proposed system. Based on these results we developed a proto- type wearable device and a cloud-server solution which we tested with regards to usability and how well the system meets our design goals. The findings suggest the proposed solution to be able to assist in the remote monitoring of the location and health condition of quarantined people, relieving work load from medical doctors as well as quarantine surveillance officials. The designed wearable device is reusable, meaning that once a patient has recovered from the disease, the same device can be used by other patient.

Keywords Monitoring of COVID-19 patients · Wearable device for remote monitoring · Pandemic control · System usability

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1 Introduction

The novel coronavirus disease (COVID-19) was first reported in December 2019 and was declared a global pandemic on March 11th 2020 by the World Health Organization [1]. As of 29 September 2021, there have been 232,636,622 confirmed cases of COVID-19, including 4,762,089 deaths, reported to WHO [2]. The most common symptoms of the disease are fever, cough and shortness of breath. Less common symptoms are aches and pains, sore throat, diarrhea, conjunctivitis, headache, loss of taste or smell, rashes on skin, and discoloration of fingers or toes [3, 4]. As the virus is transmitted from human to human through contact as well as the main transmission method is person-to-person [5], quarantine measures are an effective way to prevent it from spreading [6].

As the time from exposure and symptom onset is generally between two and 14 days [3] (average of five days), most countries made it mandatory for all travelers returning from foreign countries to stay in quarantine for two weeks. In addition, individuals were advised to adopt personal health measures such as quarantining themselves to minimize the spreading of the disease [7, 8]. While most people obediently stayed in home quarantine when instructed to do so, a proportion of people ignore the rules. Because of this, some countries resorted into enforcing quarantine laws with the help of the police or even the military. However, several countries have limited resources to ensure people with suspected infections to stay at a designated place with proper facilities [9–11]. Use of technology to monitor patients remotely to ensure quarantine may ease the tasks of law enforcing agencies. One often suggested and used method was remote surveillance through mobile phone data [12, 13]. Other suggested measured included internet of things (IoT) device, data analytic, artificial intelligence, machine learning, and robotic system [14–16].

The use of wearable devices and sensor based systems for pandemic control is natural, for example: Quer et al. [17] investigated if personal sensor data ac- cumulated over time can detect small changes that indicate infection, such as in COVID-19 patients. Shubina et al. [18] provided a brief technical review of existing contact tracing solutions and discussed the possible impact of wearable in combating the spread of a highly infectious illness. In [19], the authors suggested a new intelligent method for contact tracking and COVID-19 cluster prediction. Similarly, in [20], authors proposed a wearable bracelet to track COVID-19 pa- tients in real time. In another study, Tripathy et al. [21] proposed an Internet of Medical Things based wearable system for contact tracing to maintain social distancing to fight with COVID-19, while Tavakoli [22] theoretically discussed how the wearable technology can be used for healthcare during the COVID-19 pandemic; like augmented/virtual reality based wearable systems may facilitate to collaborate with several doctors and patients for remote diagnosis or treatment planning.

Again, it can be found that similar solutions have successfully been used before the COVID-19 pandemic to monitor, for example, the movement of Alzheimer patients and children [23], locating soldiers locations during a military operation [24], and human (women) safety band to send the emergency message with location details to the Police [25]. Again, in many countries distant monitoring with electronic devices are used as a condition of pretrial release, or post-conviction supervision, like probation or parole [26, 27]. Electronic monitoring has also been used to track juveniles [28], immigrants awaiting legal proceedings [29], adults in drug rehabilitation programs [30], and individuals accused or convicted of domestic violence [31]. Remote monitoring is used as a mechanism for reducing jail and prison populations [32]. These solutions can include feedback and alarming systems that respond to sensor input and the individuals' movement.

However, very few studies have been conducted focusing on the wearable or sensor based systems to fight against COVID-19 pandemic though a number of digital initiatives have been taken to fight with COVID-19 pandemic [33–36]. Thus, a sensor-based wearable device could be developed to assist and monitor people in quarantine during the COVID-19 pandemic. One of the established requirements for this kind of a system from the governments' perspective is that it can be used to monitor the quarantined patients. However, it remains unclear what the other major requirements of such a system would be.

Therefore, the objectives of this research are to (1) identify the requirements that need to be considered for developing a wearable device to monitor movement and health of quarantined COVID-19 patients, and (2) propose a solution based on the identified requirements. To address these research objectives, we interviewed 36 individuals including doctors, home-quarantined patients, and administrative personnel and formulated a set of design objectives. A prototype of the wearable system considering the functional requirements was then implemented and evaluated to explore the quality attributes of the proposed system.

2 Research Method

To address the research objective, we adopted a design science research (DSR) approach as guided by Vaishnavi and Kuechler [37]. The overall research method was adopted from prior similar DSR studies [38, 39] and included the following five steps: (1) awareness of problem; (2) suggestion; (3) development; (4) evaluation; and (5) conclusion. These steps are showed in Fig. 1. The process steps (first column) are linked to corresponding methods and activities of the research (second column), and the actual outcomes of the DSR are depicted in the last column. Next, we describe each of these five steps.

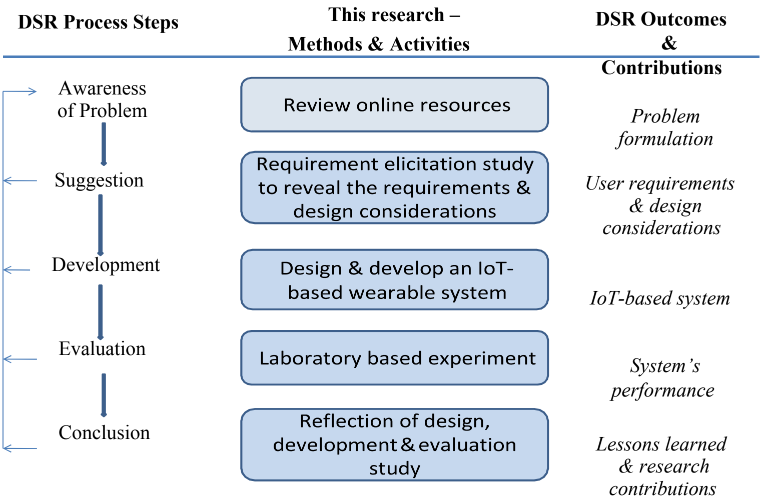


Fig. 1 Overview of the research methodology

The first step, awareness, refers to conceptualizing the situation and the problem at hand. In our case we define it as how to use technology to control, monitor and assist quarantined COVID-19 patients. Due to the novelty of the COVID-19 situation and the nature of our study, we reviewed related published research papers, online news articles, blog posts and website contents to better frame the problem [6, 40–43].

The next step is suggesting a solution to the problem. We propose developing a wearable system that could monitor and assist quarantined patients. In order to identify the requirements for such a solution we created a requirement elicitation study, interviewing 36 participants (doctors, quarantined patients and local administration personnel). The aim of these interviews was twofold: (1) to under- stand the scope of the imposed quarantines and quarantined patients' problems that could be alleviated with technology; and (2) to reveal the functional and design requirements of the law enforcement for monitoring and controlling the imposed quarantine measures.

As a third step in the process is the development of the system. We developed a rapid prototype in our lab based on the findings of step 2, and iterated the development process following agile software development recommendations. In the fourth step, we evaluated the feasibility of our solution in a laboratory environment. This process included testing the usability of the solution as well as how it matched the design goals set for the system. In the fifth and final conclusion step we present the main outcomes, contributions and open issues for further investigation and research on this topic.

3 Requirement Elicitation Study

3.1 Participants Profiles

We conducted semistructured interviews with a total of 36 people, among them five doctors, three professionals from Institute of Epidemiology Disease Control and Research (IEDCR) of Bangladesh, 17 suspected patients and 11 people who were working on local administration and had the responsibility to ensure quarantine of COVID-19 effected people. The IEDCR professionals are responsible for researching epidemiological and communicable disease in Bangladesh as well as disease control. The patients' average age was 36 years. Interviewed doctors worked at a local hospital and community clinics, and among them three were directly in charge of serving COVID-19 patients. Considering the vulnerable situation, the interviews with patients were done through telephone. Local administrative personals and professionals from IEDCR were interviewed physically.

3.2 Study Procedure

The interviews were semi-structured and were carried out in Dhaka, Bangladesh. A separate set of questions were prepared for each group of participants (patients, doctors, local administrator and personnel from IEDCR) keeping in mind the research objectives.

Participants' consent to ensure anonymity and confidentiality were collected through email or in a printed form. The Research and Development wing of authors' institute provided the ethics approval. Also, to record the audio of the interview sessions, permission was asked directly from each participant at the beginning of the interview situation. The audio recordings were later transcribed for analysis and were kept securely on trusted servers on the authors' institute.

3.3 Revealed Requirements

The transcribed interviews were analyzed qualitatively. Two researchers separately read the transcribed interview data and coded the relevant pieces of information. After the coding was completed, both researchers met together to compare the results of their coding. The inter-coder agreement [44], calculated as the sum of all the agreements divided by the sum of all agreements and disagreements was 0.89. The disagreements were resolved by discussions.

The themes revealed through the qualitative data analysis were clustered into four broad categories as showed in Table 3 in Appendix A that represents the example quotes after translation, the revealed codes and their associated categories. In the following, we describe each of these categories in detail.

1. Need for a remote monitoring and assistant system—One of the most important themes that emerged from the preliminary analysis as well as the interview data was the need for a remote monitoring and assistance system for home-quarantined people. The administrative personnel and doctors both stated that there is an inadequate number of administrative personnel to monitor and assist suspected patients, and that there is also a lack of sufficient number of resources to ensure utilities in quarantine centers and hospitals. Because of these reasons it is best for all, if suspected patients stay at home-quarantine rather than at hospitals or quarantine centers.
2. Monitoring disease specific health related data: People affected by the COVID-19 disease suffer respiratory and breathing problems [3]. The interviewed medical doctors and IEDCR personnel stated that the continuous health assessment of hospitalized and home-quarantined patients is mandatory. They stated that it is important to monitor patients' heart rate and body temperature even if they stay at self-quarantine. Thus the ability to remotely and continuously monitor patients' health was deemed as an important requirement for the system.
3. Barriers to adopt the IT-based device: The participants saw several barriers that might limit their adoption of the proposed IT-device. The two main issues were: (1) the lack of experience with technology; and (2) privacy issues. The doctors and IEDCR also raised a concern about the accuracy of health data, while the administrative personnel were afraid of potential misuse of the technology.
4. Design and functionality considerations: The following ten considerations are proposed based on the interviews: (1) accurate location tracking–an accurate time-stamped location signal is important to ensure that the patients are adequately quarantined; (2) unique identification—each quarantined person needs to be uniquely identified via the system (3) data accuracy–health related (e.g. heart rate and body temperature) data needs to be accurate and reliable to afford the making of remote health diagnosis; (4) light-weighted device—the wearable device need to be light-weighted to be comfortable to use and wear at all times; (5) easy-to-use –the device needs to be easy to use to avoid technology stress and to make using it as easy as possible; (6) easy-to-learn—similar to the ease-of-use, the use of the device should not require extensive technical know-how; (7) protect privacy—as the device is collecting sensitive information such as health and time-stamped location data, maintaining data privacy is paramount. The users' should be made fully aware who has the ability to view their data, where it is being sent and will it be deleted at some point; (8) cost-effectiveness—the development costs of the system need to be reasonable; (9) portability—the wearable system needs to be portable so that any person wearing the device may continue normal movement in their home; and

(10) reusability—the wearable system needs to be reusable, so that it can be redistributed onward to the next patients after the quarantine period is over.

The first two themes indicate the importance of staying at home quarantine. They also highlight the necessity of an assistant system for managing quarantine and to monitor health related data. The third theme highlights the barriers of using such systems by the end users. Finally, the fourth theme highlights the design and functionality considerations.

4 Proposed Wearable Device Solution

To address the system requirements identified in the elicitation study, we de- signed and built an internet-based wearable system. As a solution we propose a wearable device with an inbuilt GPS and fingerprint scanner connected to a cloud server that can provide live location to the central monitoring team. The wearable prototype system contains a heart rate monitor, temperature monitor, an internet transceiver, a display, and a feedback system, among other requirements. The system will be inexpensive and implementable for large number of susceptible patients and this will replace the need of physical monitoring.

4.1 System Architecture

Figure 2 displays overall architecture of the developed system whereas, Fig. 3 exhibits a layered architectural view of system components that are used to develop the

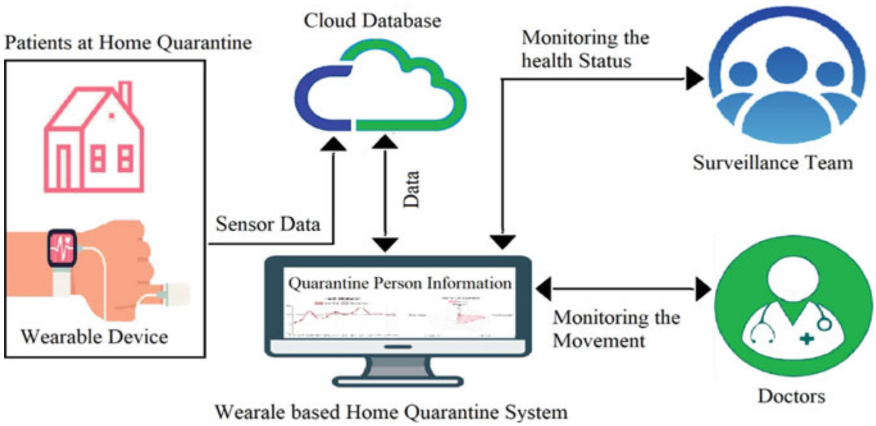


Fig. 2 An overview of system architecture

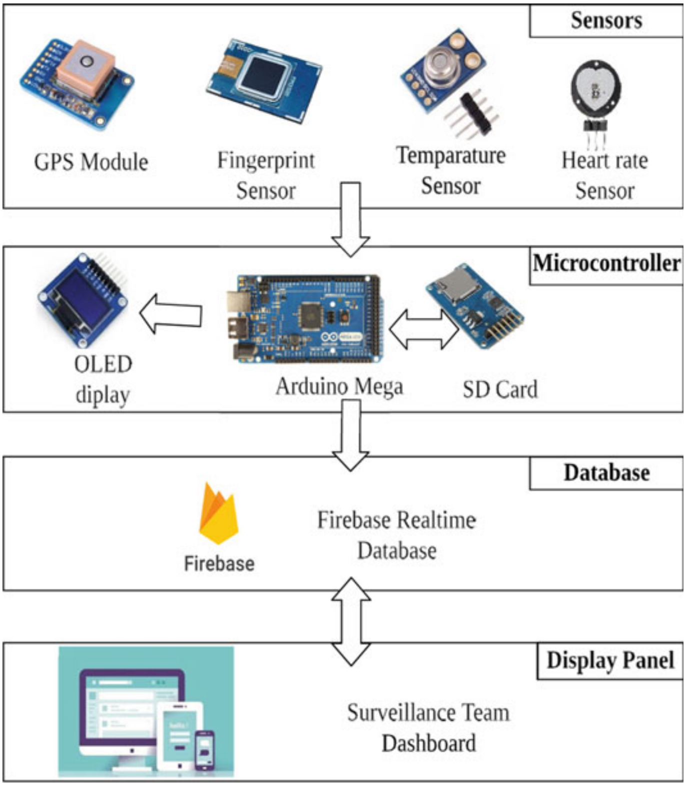


Fig. 3 A layered architectural view of system components

prototype of the system. The system consists of four sensors for measuring the (1) heart rate; and (2) body temperature; of the patient as well as for (3) fingerprint scanning; and (4) getting the user's time-stamped location. The sensors are connected to an Arduino micro-controller that also features an OLED display for visual feedback to the user. The Arduino connects to the cloud database, synchronizing the sensor data there. The medical and surveillance professionals can then access this data to ensure guidelines are met and the patient remains in good health.

4.2 Workflow of the Proposed System

Figure 4 represents the work flow of the proposed system. The wearable device is given an identification number so that in case of many devices, the surveillance team will be able to monitor each person individually. For the device to work, at first it needs to be registered with a person's unique ID, home location and fingerprint. Device will continuously capture real time location, heart rate and body temperature

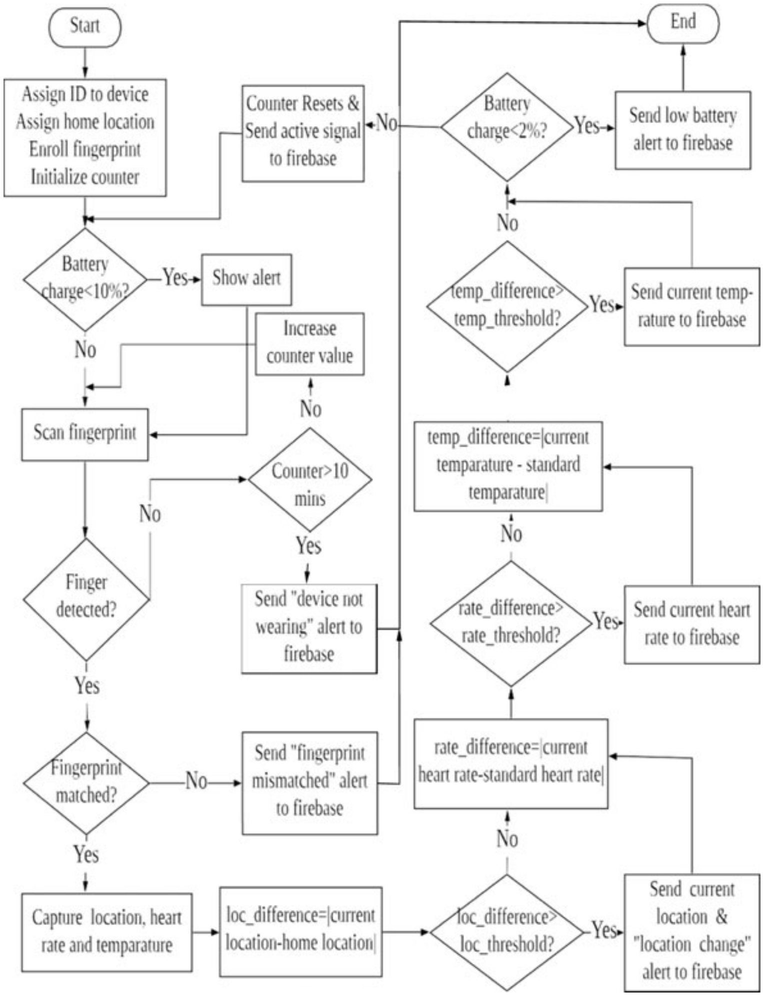


Fig. 4 System workflow diagram

of the quarantined person provided that user's real time fingerprint matched with the registered fingerprint. In case of a failure to detect a valid finger, the device will count up to 10 minutes before sending an alert to Firebase cloud based database. Captured data from the device (location, heart rate and temperature) will be continuously compared to their expected values. If any of those differences exceed their respective permitted threshold values, then the system will send the most recent data along with an alert signal (if any) to the cloud based database. For example, if the difference between quarantined person's current location and home location exceeds a permitted threshold value, a ”location change alert” along with current location will be sent to the cloud. Also, in case there are systematic changes in the heart rate or body temperature, the system will send the current heart rate or body temperature to the cloud.

Regardless, the device has any data (location, heart rate, temperature) or alert to send to the cloud or not, the device will send an active signal to the cloud continuously which will ensure that the device is active.

This device will run by DC (direct current) power supply supported by a battery. So after a fixed time, the device needs to be charge. When charge the device has less than 10% battery left, an emergency light associated with the device will turn on, and it will remain on, until the device is plugged in with the charger. When the battery life of the device goes extremely low (2%) the device will send an alert signal to the cloud before turning off so that the surveillance team can be dispatched to look into the situation. As charging the device is an issue, each person will be given two wearable devices, so that while one is in charging, other one can be used. This way, continuous monitoring of quarantined people will be ensured.

4.3 Prototype Development

The prototype development was divided into two parts: (1) the hardware device and related software; and (2) the cloud monitoring system. In this section we present the development of both.

Developing the Hardware Device: The proposed system includes two bio- signal sensors to obtain the health related data that includes: (a) pulse sensor (SEN-00162)—a plug-and-play heart-rate sensor for Arduino to find the pulse rate as heart bit per minute (bpm), and (b) a temperature sensor (GY-906 MLX90614ESF)—to measure and send the body temperature. Similarly, other two surveillance related sensors were used: (a) fingerprint sensor (AS608) having three levels of features like pattern, minutiae points, and pores and ridge shape for recognition purposes; and (b) a GPS sensor (GY-NEO-6M V2) to keep the track of the patients who are in quarantine. For showing notifications to user, an OLED display (DIS-0091) is used. Apart from these; an Arduino Mega (mi-crocontroller board) was used as a processing unit that intelligently controls the other sensors. All the sensors are directly connected with micro controller board in different pins. After recognizing the user through the fingerprint sensor, the microcontroller takes analog data from GPS, temperature and heart rate sensors. These data are then sent to the cloud-based database. A 9V battery (MIS-00004) is used to give power to the device. The key functionalities of the proposed system and associated logics to ensure proper data flow to the cloud based surveillance system is shown in Algorithm 1.

Algorithm 1: FingerCap

```
Initialization of sensors, display, counter;
while true do
    if battery.charge() ≤ 10 percent then
        display("ALERT!! Low battery");
    end
    if fingerprint.detect_valid_finger() then
        if fingerprint.matched_enrolled_finger() then
            capture(location,heart rate,temperature,timestamp); loc
            difference=|location - home location|;
            rate difference=|heart rate-std heart rate|;
            temp difference=|temperature-std temperature|;
            if loc_difference ≥ loc_threshold then
                firebase.send_data(ID, location, timestamp);
                firebase.send_alert(ID,"location change",timestamp);
            end
            if rate_difference ≥ rate_threshold then
                firebase.send_data(ID,heart rate,timestamp);
            end
            if temp_difference ≥ temp_threshold then
                firebase.send_data(ID,temperature,timestamp);
            end
            if battery.charge() ≤ 2 percent then
                firebase.send_alert(ID,"Battery low",timestamp);
                break;
            else
                counter=0;
            end
        else
            firebase.send_alert(ID,"fingerprint mismatched",timestamp);
            break;
        end
    else
        if counter ≥ 10min then
            firebase.send_alert(ID,"Device not wearing", timestamp);
            break;
        else
            counter=counter+1;
        end
    end
end
```

In the Algorithm 1, at first, battery charge of the device will be checked. In case, battery charge is low, the user will get an alert through the Organic Light Emitting Diode (OLED). Next, the fingerprint scanner will try to scan continuously the fingerprint of user. If no fingerprint is detected, then the counter will stay on and the device will count until 10 minutes has passed. After this, the device will send an alert to the surveillance team that the device is inactive. If the fingerprint is detected, the system will check whether it matches with the initially given fingerprint of the user or not. If it does not match with the given fingerprint, the device will send an alert to the surveillance team again. Next, the device will capture the present location, heart rate and temperature of the user and send it to the cloud server. This loop is then repeated.

Dashboard for the surveillance team: A Graphical User Interface based dashboard or system, which is connected with the cloud based database, is capable of presenting all data received from multiple wearable devices. A few prototypical interfaces of the dashboard are displayed in Figs. 5 and 6 in Appendix B. This interface can be used by the surveillance team as well as medical doctors to access the sensitive information of the patients. As such, it requires an authentication via a password and a username. Through the monitoring interface personnel can look up statistics of individual users as well as overall statistics of all who are followed with the wearable sensors. The visual dashboard (Fig. 6) is complementary to the automatic warnings that are sent out by the wearable devices in case they are disconnected or the patients break quarantine.

5 Evaluating the Prototype

A lighted weighted evaluation study was conducted at Software Engineering Laboratory at authors' institute to measure the functional accuracy and the usability of the proposed system. For each primary feature/function of the system, a test case scenario was prepared and then conducted five times. The percent of the success rate and the average delay in seconds are showed in Table 1. With the exception of the fingerprint mismatch and the capturing the current location, all other functionalities cleared the tests.

We then set out to evaluate the system's usability. Five faculty members were invited as a test subjects. During the evaluation study, firstly a brief presentation about the objective of this study was given to the participants. Second, the proposed system was demonstrated to them and they were given the opportunity to use the system for roughly 5 minutes. Finally participants were asked to perform a set of tasks with the system. Finally they were asked to provide their opinion about the usability and effectiveness of the proposed system, and give any recommendations they might have come up with. A brief summary of the recorded data is given in Table 2.

The results showed that each participant was able to perform the designated tasks with comparatively minimum number of attempts (see Table 2). For example, for 40% (4 out of 10 tasks) tasks participants did not ask any questions from the observing researchers. A similar result was found for the number of at- tempts. Except for the task number six, all other tasks took less than or around half a minute to complete. The participants also viewed the graphical results generated by the tool during their testing and generally said that it would be an efficient way for the doctors to remotely monitor quarantined persons. All the participants were satisfied with this system, and expressed that the overall usability of the system was good. According to them, the system would be easy to learn for the surveillance team members as well.

Table 1 Results of the evaluation study (functional accuracy test)

Task name	Test-case description	% of success	Delay (Second) M ± SD
(a) Monitoring heart rate	How the users data are received/visualize in the system's dashboard	100%	10.0 ± 0.632
(b) Monitoring temperature		100%	3.4 ± 0.8
(c) Capturing location		80%	3.2 ± 0.74
(d) Fingerprint mismatch alert	If the real time fingerprint don't match with the quarantine person's fingerprint, it gives alert to the dashboard	80%	3.6 ± 0.48
(e) Not wearing alert	If the quarantine person is not wearing the device, it gives alert to the dashboard	100%	3.8 ± 0.78
(f) Low battery alert	If the device's battery is less than 2%, it gives alert to the dashboard	100%	2.0 ± 0.632
(g) Low battery notification to user	If the device's battery is less than 10%, it gives alert to the user (quarantine person)	100%	1.4 ± 0.4898
(h) Location change alert	If the quarantine person move outside the designated area, it gives alert to the dashboard	100%	5.0 ± 0.632

6 Conclusions

This study presented the empirical design and implementation of a wearable de- vice for monitoring the health and physical location of quarantined COVID-19 patients. Using DSR, we first conducted a qualitative interview study for identifying the design requirements of such a system. Then based on our findings, we iteratively developed a prototype. We evaluated the prototype from two perspectives: (1) how well it takes into account the design goals; and (2) usability. Based on our findings, the developed wearable system coupled with the cloud-server connection is a practical and useful solution for assisting health professionals and government officials in pandemic control and situation monitoring.

Our study has the following limitations. First, the developed prototype was not yet put in the form of an actual wearable device. While the basic system and usability requirements were met, additional testing with the next phase of the prototype is still needed before moving into production. Second, affordability of the device was prioritized. The prototype was cost-effective, meaning that better results may be achieved in case the cost of the system is not an issue. Third, some aspects of the system such as using it while taking a shower or using it while sleeping were not

Table 2 Results of the evaluation study (system usability)

Task	Number of attempts ($M \pm SD$)	Task completion time (second) ($M \pm SD$)	Number of times asking help ($M \pm SD$)
T1: Log in to the system using given credentials	1 ± 0	10.2 ± 1.72	0 ± 0
T2: Find list of all home quarantine people in Mirpur area	1 ± 0	10.8 ± 1.46	0 ± 0
T3: Find statistical information of all home quarantine people in Dhaka region	1 ± 0	10.6 ± 1.85	0 ± 0
T4: Enroll a new home quarantine person in the system	1.2 ± 0.4	28.6 ± 2.57	0.2 ± 0.4
T5: Remove a quarantine person from the system	1 ± 0	5.4 ± 1.01	0 ± 0
T6: Contact a quarantine person in Mirpur area whose location has been changed	1.6 ± 0.8	131.8 ± 7.90	0.6 ± 0.8
T7: Notify doctor for a person in Mirpur area whose heart rate and temperature is high	1.8 ± 0.74	31.2 ± 2.31	0.8 ± 0.74
T8: Notify nearby police for a person in Mirpur area whose location has been changed and who is contacted previously	1.6 ± 0.8	39.6 ± 3.00	0.6 ± 0.8
T9: Find number of persons in a particular area who are not currently wearing the device	1.4 ± 0.48	11 ± 1.41	0.4 ± 0.48
T10: Save health information graph of Mr. X in pdf format and e-mail it to a concerned doctor	1.6 ± 0.8	28.2 ± 2.31	0.6 ± 0.8

tested. The shower problem might be solved by simply asking users to take showers that are shorter than 10 min, or by making the device waterproof. The problem with sleeping with the device is the fingerprint scanning requirement. The device needs to be fitted so that the fingerprints are scanned automatically at all times and does not require any additional work from the user. Fourth, a central cloud based database is used in the system which may get downed by receiving data from a large number of devices. In future, for implementing the system for a large number of areas, separate interconnected databases shall be maintained for each of the areas rather keeping a central database. Finally, constant internet connection is a mandatory requirement for this device to work. This means that continuous monitoring will not be ensured in case of having no internet connection.

We regard our findings promising as in the interviews all stakeholders viewed the idea as positive and the evaluation of the prototype was also considered a success. Our future work will focus on developing the concrete version of the system along with conducting an extensive evaluation study involving home quarantine people and members of the surveillance team. The developed technology may be adopted to be in use also after the COVID-19 pandemic is over in, for example, the monitoring of the health and location of Alzheimer patients.

7 Example Interview Responses

See Table 3.

8 Prototype of User Interfaces

See Figs. 5 and 6.

9 Example Questionnaire

9.1 Questions to Patients

1. Tell us about yourself and your family.
2. Tell us about your IT resources at home (e.g., PC, smartphone, Internet connection).
3. Have you ever used any kind of wearable device?
4. Will you be comfortable to use a wearable device while you are in home quarantine?

Table 3 The categories and codes with example quotes from interview

Categories	Codes	Example quotes (after translation)
Need for an IT based home quarantine system	Quarantine	"All returnees from abroad will be checked and will remain under a two-weeks mandatory quarantine" [participant from IEDCR]
	Distant surveillance	"Maintaining proper quarantine at home is very difficult in the social context of Bangladesh. Distant surveillance is required." [participant from IEDCR] "Monitoring every home quarantined person is very difficult by current system Distance monitoring system will be very much useful" [local administrator]
	Lack of quarantine centers	"Throughout the country there are limited quarantine centers for suspected persons mainly due to the limited time and resources" [local administrator]
	Lack of administrative personals	"It is not possible to effectively monitor all the persons who are in quarantine centers due to lack of human resource." [local administrator]
	Lack of resources	"It requires a lot of resources to ensure proper utilities to all persons staying in quarantine centers, In some cases, it may not be possible to arrange the require services in time" [local administrator]
Monitoring disease specific health related data	Body temperature	"We need to check the body temperature of COVID-19 patient to understand the current health status of the patient." [Doctor]
	Heart rate	"Heart rate monitoring is important to understand the possibility of cardio vascular disease that may take place due to COVID-19″ [Doctor]
	Blood pressure	"Patients with hypertension appear to be at a higher risk of dying from COVID-19" [Doctor]

(continued)

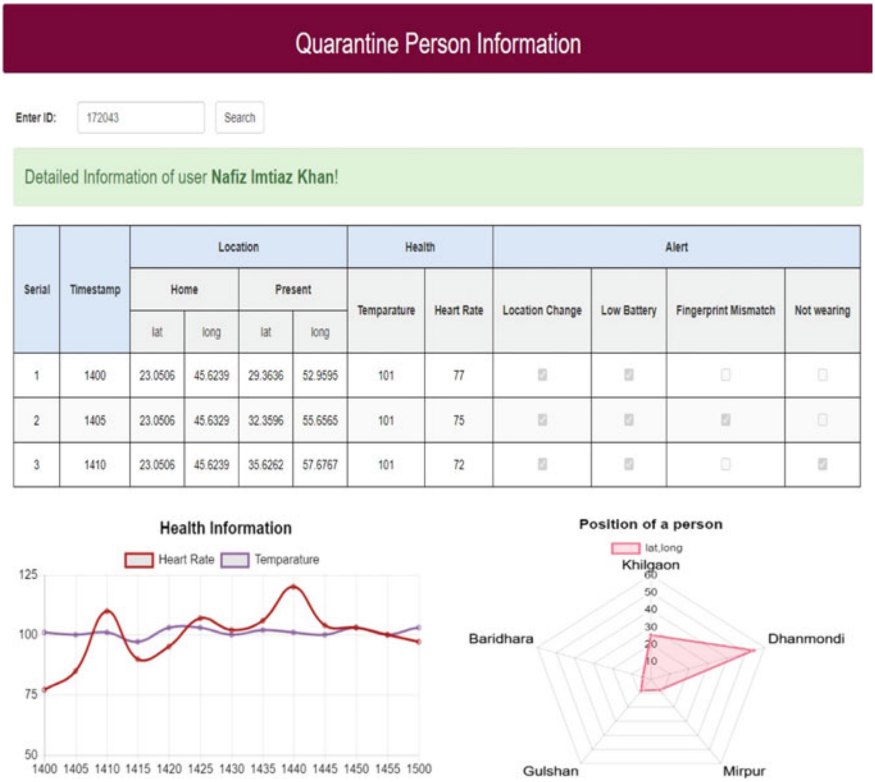
Table 3 (continued)

Categories	Codes	Example quotes (after translation)
	Blood oxygen level	"COVID-19 is killing with silent hypoxia: Patients' oxygen levels fall dangerously low but they don't have shortness of breath that usually signals the life-threatening condition; hence blood oxygen level of the patients shall be monitored" [Doctor]
	ECG	"ECG need to be monitored for infected COVID-19 patients having heart disease It can be used to investigate symptoms of a possible heart problem, such as chest pain, palpitations (suddenly noticeable heartbeats), dizziness and shortness of breath." [Doctor]
	Respiratory rate	"Respiratory rate is one of the most important metric to monitor if someone is infected by COVID-19″ [Doctor]
Barriers to adopt the IT based device	Lack of Technology experience	"I am not familiar with using wearable devices. That's why it will be very much difficult for me to use that kind of wearable device." [Patient]
	Wearing for long time	"Wearing a device for a long time will very much disturbing for me and I will not be comfortable with this while sleeping or in relaxation time." [Patient]
	Charging	"Due to a lot of load shedding in my locality, it will be very much challenging for me to charge the device properly." [Patient]
	Internet connectivity	"In my home I don't have internet connection. Also, it will not be possible for me to be within internet connected area all the time." [Patient]
	Continuous monitoring	"I will feel very much uncomfortable if I know that I am continuously being monitored by local authorities for consecutive days" [Patient]

(continued)

Table 3 (continued)

Categories	Codes	Example quotes (after translation)
Design and functionality considerations	Accurate position	"We need to check whether the infected patients are staying at their respective home address or not" [Local Administrator]
	Unique identification	"Each patient must have an unique identification number, otherwise it will not be possible for us to monitor each patient uniquely" [Local Administrator]
	Data accuracy	"Data collected from each device must have to be accurate for remote health diagnosis" [Doctor]
	Light weighted device	"If the wearable device is light-weighted, then I will be comfortable to use that device continuously while staying in home quarantine," [Patient]
	Easy-to-use	"System usability should be given high priority for designing such kind of monitoring system, so that by little training a surveillance team can be formed." [Local Administrator]
	Easy-to-learn	"System should be designed in such a way that any new user can easily learn the functionalities of the system" [Local Administrator]
	Protect privacy	"No one should have access to the patients' health data except the surveillance team and the concerned doctors." [Local administrator]
	Cost effectiveness	"Development cost of the device shall be considered for large scale production" [Local administrator]
	Portability	"Device shall be portable so that while wearing the device patient can carry on his/her normal movement" [participant from IEDCR]
	Reusability	"Device need to be reusable so that it can be given to another person after fourteen days" [Local administrator]



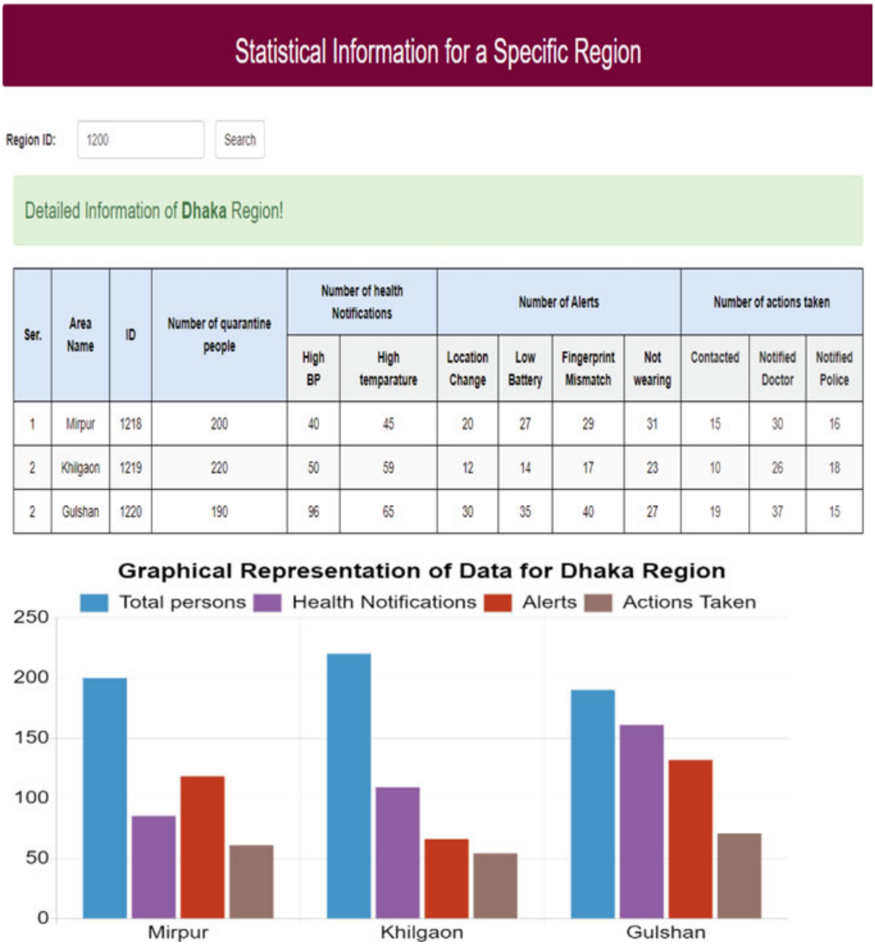
Serial	Timestamp	Location				Health		Alert			
		Home		Present		Temparature	Heart Rate	Location Change	Low Battery	Fingerprint Mismatch	Not wearing
		lat	long	lat	long						
1	1400	23.0506	45.6239	29.3636	52.9595	101	77				
2	1405	23.0506	45.6329	32.3596	55.6565	101	75				
3	1410	23.0506	45.6239	35.6262	57.6767	101	72				

Fig. 5 User interface to show the information of a quarantine person

5. How do you feel about the situation that you have been staying in home quarantine and are constantly being monitored rather staying in isolation centers?
6. How important it is for you that the surveillance team constantly monitors your activity if you are infected with COVID-19?

9.2 Questions to Doctors

1. What are the challenges and limitations you feel serving in a pandemic situation?
2. What are the risks you have while you are treating patients affected by a highly contagious virus?
3. If a COVID-19 infected patient is staying in home, what are the health parameters that need to be checked frequently?
4. What do you think about remote health diagnosis? To what extent do you think it is effective in a pandemic situation?



Ser.	Area Name	ID	Number of quarantine people	Number of health Notifications		Number of Alerts				Number of actions taken		
				High BP	High temparature	Location Change	Low Battery	Fingerprint Mismatch	Not wearing	Contacted	Notified Doctor	Notified Police
1	Mirpur	1218	200	40	45	20	27	29	31	15	30	16
2	Khilgaon	1219	220	50	59	12	14	17	23	10	26	18
2	Gulshan	1220	190	96	65	30	35	40	27	19	37	15

Fig. 6 User interface to show the statistical information of a specific region

5. What are the criteria on which you classify condition of a patient as critical?
6. Why do you think temperature and heart rate need to be checked frequently?

9.3 *Questions to Administrative Personals*

1. Please explain the current challenges that you are facing to fight the pan- demic.
2. How do local administration ensure that all the suspected patients are main taining home quarantine properly?
3. To what extent do you think that any wearable device can be helpful to constantly monitor the activity of home quarantine people?

4. What things shall be considered for developing a home quarantine surveillance system for minutely monitoring the health and the movement of quar- antined COVID-19 patients?

9.4 Questions to IEDCR Personals

1. What guidelines are you giving to the persons who return from abroad?
2. How do you monitor the health condition of a suspected person?
3. How useful the central surveillance system is to efficiently monitor the suspected patients?
4. What functionalities the central surveillance system should have in order to monitor the health and movement of quarantined COVID-19 patients?

References

1. Laato, S., Najmul Islam, A.K.M., Islam, M.N., Whelan, E.: What drives unverified information sharing and cyberchondria during the covid-19 pandemic? Eur. J. Inf. Syst. 1–18 (2020)
2. WHO Coronavirus (COVID-19) Dashboard. Available on https://covid19.whoint. Last accessed 30 Sept 2021
3. Larsen, J.R., Martin, M.R., Martin, J.D., Kuhn, P., Hicks, J.B.: Modeling the onset of symptoms of covid-19. Frontiers Public Health **8**, 473 (2020)
4. Utku, A.C., Budak, G., Karabay, O., Gu¨¸clu¨, E., Okan, H.D., Vatan, A.: Main symptoms in patients presenting in the covid-19 period. Scottish Med. J. **65**(4), 127–132 (2020)
5. Toit, A.D.: Outbreak of a novel coronavirus. Nat. Rev. Microbiol. (3), 123–123 (2020)
6. Wilder-Smith, A., Freedman, D.O.: Isolation, quarantine, social distancing and community containment: pivotal role for old-style public health measures in the novel coronavirus (2019-ncov) outbreak. J. Travel Med. (2020)
7. A Farooq, S Laato, and AKMN Islam. The impact of online information on self- isolation intention during the covid-19 pandemic: A cross-sectional study. *Journal of Medical Internet Research*, 2020.
8. Islam, M.N., Inan, T.T., Najmul Islam, A.K.M.: Covid- and the rohingya refugees in bangladesh: the challenges and recommendations. Asia Pac. J. Public Health **32**(5), 283–284 (2020)
9. Eskeziya, A., Endashaw, H. et al.: Poor sleep quality and associated factors among individuals in covid-19 quarantine center, southern ethiopia, 2020. J. Mental Health Issues Behav. (JMHIB) **1**(01), 1–11 (2021). ISSN: 2799–1261
10. Haque, A.: The covid-19 pandemic and the public health challenges in bangladesh: a commentary. J. Health Res. **34**, 563–567 (2020)
11. Udaya Bahadur, B.C., Pokharel, S., Munikar, S., Wagle, C.N., Adhikary, P., Shahi, B.B., Thapa, C., Bhandari, R.P., Adhikari, B., Thapa, K.: Anxiety and depression among people living in quarantine centers during covid-19 pandemic: a mixed method study from western nepal. PloS One **16**(7), e0254126 (2021)
12. Arni, S.R., Rao, S., Vazquez, J.A.: Identification of covid-19 can be quicker through artificial intelligence framework using a mobile phone-based survey in the populations when cities/towns are under quarantine. Infect. Control Hospital Epidemiol. 1–18 (2020)
13. Islam, M.N., Islam, I., Munim, K.M., Najmul Islam, A.K.M.: A review on the mobile applications developed for covid-19: an exploratory analysis. IEEE Access **8**, 145601–145610 (2020)

14. Islam, M.N., Najmul Islam, A.K.M.: A systematic review of the digital interventions for fighting covid-19: The bangladesh perspective. IEEE Access **8**, 114078–114087 (2020)
15. Ting, D.S.W., Carin, L., Dzau, V., Wong, T.Y.: Digital technology and covid-19. Nat. Med. 1–3 (2020)
16. Islam, M.N., Inan, T.T., Rafi, S., Akter, S.S., Sarker, I.H., Najmul Islam, A.K.M.: A systematic review on the use of ai and ml for fighting the covid-19 pandemic. IEEE Trans. Artif. Intell. (2021)
17. Quer, G., Radin, J.M., Gadaleta, M., Baca-Motes, K., Ariniello, L., Ramos, E., Kheterpal, V., Topol, E.J., Steinhubl, S.R.: Wearable sensor data and self-reported symptoms for covid-19 detection. Nat. Med. **27**(1), 73–77 (2021)
18. Shubina, V., Ometov, A., Lohan, E.S.: Technical perspectives of contact-tracing applications on wearables for covid-19 control. In: 2020 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), pp. 229–235. IEEE (2020)
19. Jahmunah, V., Sudarshan, V.K., Oh, S.L., Gururajan, R., Gururajan, R., Zhou, X., Tao, X., Faust, O., Ciaccio, E.J., Ng, K.H., et al.: Future iot tools for covid-19 contact tracing and prediction: a review of the state-of-the-science. Int. J. Imaging Syst. Technol. **31**(2), 455–471 (2021)
20. Weizman, Y., Tan, A.M., Fuss, F.K.: Use of wearable technology to enhance response to the coronavirus (covid-19) pandemic. Public Health **185**, 221 (2020)
21. Tripathy, A.K., Mohapatra, A.G., Mohanty, S.P., Kougianos, E., Joshi, A.M., Das, G.: Easy-band: a wearable for safety-aware mobility during pandemic outbreak. IEEE Consum. Electron. Mag. (2020)
22. Tavakoli, M., Carriere, J., Torabi, A.: Robotics, smart wearable technologies, and autonomous intelligent systems for healthcare during the covid-19 pandemic: an analysis of the state of the art and future vision. Adv. Intell. Syst. 2000071 (2020)
23. Karasikov, N., Tamir, D., Bar-On, R.N.: Remote monitoring system for alzheimer patients. US Patent App. 11/913,439
24. Islam, M.N., Rabi-Ul Islam, M., Rafiqul Islam, S.M., Bhuyan, S.A., Hasib, F.: Locsoldiers: towards developing an emergency troops locating system in military operations. In: 2018 4th International Conference on Electrical Engineering and Information and Communication Technology (iCEEiCT), pp. 264–267. IEEE (2018)
25. Islam, M.N., Promi, N.T., Shaila, J.M., Toma, M.A., Pushpo, M.A., Alam, F.B., Khaledur, S.N., Anannya, T.T., Safeband, M.F.R.: A wearable device for the safety of women in bangladesh. In: Proceedings of the 16th International Conference on Advances in Mobile Computing and Multimedia, pp. 76–83 (2018)
26. Black, M., Smith, R.G.: Electronic Monitoring in the Criminal Justice System (2003)
27. Di Tella, R., Schargrodsky, E.: Criminal recidivism after prison and electronic monitoring. J. Polit. Econ. **121**(1), 28–73 (2013)
28. Roy, S.: Five years of electronic monitoring of adults and juveniles in lake county, Indiana: a comparative study on factors related to failure. J. Crime Justice **20**(1), 141–160 (1997)
29. Marouf, F.E.: Alternatives to immigration detention. Cardozo L. Rev. **38**, 2141 (2016)
30. Howell, J., Nag, A., McKnight, M., Narsipur, S., Adelegan, O.: A low-power wearable substance monitoring device. In: 2015 IEEE Virtual Conference on Applications of Commercial Sensors (VCACS), pp. 1–9. IEEE (2015)
31. Erez, E., Ibarra, P.R., Lurie, N.A.: Electronic monitoring of domestic violence cases-a study of two bilateral programs. Fed. Probation **68**, 15 (2004)
32. Payne, B., Gainey, R.: The electronic monitoring of offenders released from jail or prison: safety, control, and comparisons to the incarceration experience. Prison J. **84**, 413–435 12 (2004)
33. Zaman, A., Islam, M.N., Zaki, T., Hossain, M.S.: Ict intervention in the containment of the pandemic spread of covid-19: an exploratory study (2020). arXiv:2004.09888
34. Azim, A., Islam, M.N., Spranger, P.E.: Blockchain and novel coronavirus: towards preventing covid-19 and future pandemics. Iberoam. J. Med. **2**(3), 215–218 (2020)

35. Khan, S.R., Rownok, M.R.A., Prithula, S.R., Rifat, F.Y., Islam, N.N., Islam, M.N.: mvote: A mobile voting system to conduct election during covid-19 pandemic. In: 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), pp. 235–238. IEEE (2020)
36. Islam, M.N., Khan, S.R., Islam, N.N., Rownok, M.R.A., Zaman, S.R., Zaman, S.R.: A mobile application for mental health care during covid-19 pandemic: development and usability evaluation with system usability scale. In: International Conference on Computational Intelligence in Information System, pp. 33–42. Springer, Berlin (2021)
37. Vaishnavi, V.K., Kuechler, W.: Design Science Research Methods and Patterns: Innovating Information and Communication Technology. CRC Press (2015)
38. Chatterjee, S., Byun, J., Dutta, K., Pedersen, R.U., Pottathil, A., Xie, H.: Designing an internet-of-things (IOT) and sensor-based in-home monitoring system for assisting diabetes patients: iterative learning from two case studies. Eur. J. Inf. Syst. **27**(6), 670–685 (2018)
39. Meth, H., Mueller, B., Maedche, A.: Designing a requirement mining system. J. Assoc. Inf. Syst. **16**(9), 799 (2015)
40. Blendon, R.J., DesRoches, C.M., Cetron, M.S., Benson, J.M., Meinhardt, T., Pollard, W.: Attitudes toward the use of quar- antine in a public health emergency in four countries: the experiences of hong kong, singapore, taiwan, and the united states are instructive in assessing national responses to disease threats. Health Affairs **25**(Suppl1), W15–W25 (2006)
41. Majumder, S., Mondal, T., Deen, M.J.: Wearable sensors for remote health monitoring. Sensors **17**(1), 130 (2017)
42. Shehav-Zaltzman, G., Segal, G., Konvalina, N., Tirosh, A.: Remote glucose monitoring of hospitalized, quarantined patients with diabetes and covid-19. Diabetes Care **43**(7), e75–e76 (2020)
43. Unger, J.D.: System for monitoring patient location and data. US Patent 5,458,123 (1995)
44. Miles, M.B., Huberman, A.M.: Qualitative Data Analysis: An Expanded Sourcebook. Sage (1994)

Context-Aware and User Adaptive Smart Home Ecosystems Using Wearable and Semantic Technologies During and Post COVID-19 Pandemic

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Abstract In recent years, technology-based health programs, including context-aware and user-adaptive smart home ecosystems, have shown tremendous potential to limit disparities in healthcare access and improve uptake in health programs, thereby improving health outcomes. In this chapter, we review the potential use and applications of context-aware and user-adaptive smart home ecosystems to support the diagnosis, monitoring and management of health conditions. Further, we also discuss the barriers and limitations of using wearable and smart home technologies, their facilitators, current gaps and future opportunities. The chapter provides evidence-based applications and a comprehensive understanding of the use of wearables and smart home ecosystems during and after COVID-19 pandemic for health care providers, researchers, students, and technology developers.

Keywords Context-aware · COVID · Ecosystems · Semantic · Smart home · Wearable

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1 Introduction

COVID-19 has evolved into a pandemic with almost 14 million cases and 600,000 deaths worldwide [1]. Unsurprisingly, during this pandemic, governments and public health authorities have implemented strict restrictions on movement to limit community transmission and have implemented strict efforts to control the pandemic such as hand washing, isolation, quarantining and social distancing [2]. Despite these efforts, the pandemic has had a significant impact on healthcare systems' capacity to continue to deliver essential health services, especially to vulnerable populations such as older adults, children, people living with chronic conditions, people living with disabilities and minorities [3].

In recent years, technology-based health programs have shown tremendous potential to limit healthcare access disparities and improve uptake in health programs, thereby improving health outcomes [4–10]. The success of technology-based programs has been attributed to their ability to overcome many health and social care challenges, as it generates new living spaces that combine the latest technologies with social environments to enhance the quality of life, independence, and health outcomes [11]. Indeed, the successes of these programs can provide a roadmap to people in desperate need to access healthcare services during the COVID pandemic, especially at the comfort of the individual's home, and hence been studied by several researchers in the past few months [12–17].

There is a rising need to bridge the home and healthcare setting gap, considering most individuals with chronic conditions and disabilities receive almost no care at home, where they spend most of their time [18, 19]. One such technology that could assist in providing care is Smart Home. The concept of Smart Home involves specifically designed living spaces to offer unobstructed support systems and interactive technologies to promote improved well-being, participation and independence that otherwise cannot be afforded [20]. However, the challenge involved in smart home technologies is ensuring it is safe and secure to disabilities, stress, falls, fear and/or social isolation [20]. Hence, these technologies have been integrated with numerous sensors to identify users' activity and provide a context-aware, user-adaptive and user-friendly function to support individuals without obstructing their normal activities [21–23]. An example of such a sensor is based on wearable technology.

Wearable technologies have recently gained considerable importance in both the application and research field as a means to monitor and track individuals and promote rehabilitation, surveillance and human–computer interaction [24]. Studies suggest that these low-cost technologies have a great potential to help monitor human activity and well-being in inherently noisy and complex environments to improve health outcomes and Activities of Daily Living (or ADLs), especially for older people or people with cognitive improvements [9, 25]. As a result, these technologies have long been considered solutions to support and promote independent living and healthy ageing [26], especially in smart home applications.

In this study, we defined a smart home ecosystem as 'a an information technology system using a combination of context-aware and user-adaptive techniques that acquire data from wearables to support the individual's healthcare needs both during and post-pandemic'. The smart home ecosystem involves user modelling and adaptation based on contextual awareness, including fuzzy personas and semantically linked models. This would enhance the individual's ability to improve health outcomes at home without obstructing independence and daily activities. Moreover, it would allow for efficient knowledge representation of the ecosystem using semantic technologies that medical professionals can utilise to make informed remote decisions regarding their health needs.

In this book chapter, we reviewed the potential use and applications of context-aware and user-adaptive smart home ecosystems to support the diagnosis, monitoring and management of health conditions. Further, we also discussed the barriers and limitations of wearable and smart home ecosystems, their facilitators, current gaps and future opportunities.

2 Smart Home Eco-Systems in Healthcare

A smart home ecosystem refers to a home environment equipped with information and communication technologies such as household devices, sensors and communication networks that can be remotely controlled, accessed and monitored to support the residents' needs [27]. This concept was initially designed to improve the users' level of comfort, security and energy efficiency. However, over the years, smart home ecosystems have been used to address a myriad of user needs such as comfort, convenience and user-friendliness [28] with the introduction of modernized sensors [29].

According to De Silva et al. [30] the smart home ecosystem can be divided into three categories based on their application. The first category looks at detecting and recognizing the actions of its resident to support their needs. The second category looks at storing and retrieving data captured within the smart home. Finally, the third category aims towards processing the data collected to forecast and alert residents regarding upcoming disasters or concerns. These categories can be further extended to reducing the overall energy consumption of the house by monitoring the activity of the resident and controlling and rescheduling the operating times to reduce energy supply and demand.

Several studies in the literature have implemented smart home ecosystems to create a sense of well-being and high quality of life for its users. For example, Arcelus et al. [31] developed an automated system of intelligent sensors that monitors the health and well-being of the elderly to provide them unobtrusive support with comfort and an independent lifestyle at an affordable cost. Chen, Pomalaza-Raez [32] implemented a low-cost wireless body sensor system to monitor the vital physiological signs of a person living at home, specifically human body movements measured through a waist-mounted triaxial accelerometer. Pham et al. [33] developed a cloud-based smart home environment that collected data from non-invasive sensors, including the residents' location and daily activities. They stored data in the cloud as textual information, which healthcare professionals could access in real-time. Jung [34] designed a smart home hybrid-aware model that collects data from environmental and biosensors and stores the data on a cloud-based server. The server analyses the data using machine learning algorithms to determine the activity of the elderly and monitor factors that may impact their health. Giovani Rubert et al. [35] and Freitas et al. [36] implemented a pervasive smart home system to monitor the vitals of a sick person using sensors, which was stored and analysed on the cloud to enhance medical services at home. Li [37] focused on limiting the obstacles faced by out-of-home medical visits such as time, effort and cost to travel by using the latest sensor technologies to collect vital patient data from the smart home environment. Data were transferred via the internet to healthcare systems, where medical practitioners can access them to provide real-time monitoring and intercept and respond quickly to medical emergencies. Similar methods were implemented in numerous other smart home technologies. These methods included capturing data from various sensors, storing and processing the data in a remote server and providing necessary feedback.

2.1 Benefits of Smart Home Eco-Systems in Healthcare

Smart home ecosystems have the potential to enhance home care for the elderly, people with chronic conditions and people with disabilities [38] due to their ability to maintain health and prevent loneliness amongst these individuals [39]. The power of smart home ecosystems to maintain health has been attributed to the advancement in intelligent systems [29] that enables monitoring, operational efficiency, management and consultancy [40]. For example, remote health monitoring allows for immediate health care and access to medical services within the smart home, or robotic devices assists individuals with disabilities achieve long and healthy lives [39].

The benefits of smart home ecosystems are evident in the clinical outcomes of the people living within these homes. Kelly [41] demonstrated the increased quality of life, reduced hospital readmissions, reduced length of stay in the nursing home and reduced length of stay in hospitals for individuals using smart home systems. In the study by Skubic et al. [42], residents who utilized sensors within a smart home ecosystem reported feeling safer. At the same time, their family members indicated that they were satisfied knowing that someone was watching over their loved ones. Further, Tomita et al. [43] reported better physical and cognitive status in older people using smart home systems, with 91% recommending its use to others.

2.2 Challenges in Smart Home Implementations

While the smart home ecosystem has numerous benefits in healthcare, designing a functional smart home is not without its challenges. Hence, additional research is needed to improve the overall performance and reliability of the system, thereby improving market penetration and acceptance.

The literature highlights three critical challenges associated with smart home systems. The first one is the need for *interoperability*. Smart home ecosystems rely on connection with numerous devices, sensors and communication networks. Interoperability is one of the critical aspects to ensure all components smoothly function together [44]. This is because most devices are built with different operating systems, hardware, programming systems, standards and communication protocols that may affect how data is exchanged. Therefore, there is a need for systems and devices to have similar protocols to ensure the proper execution of tasks [9, 45, 46].

The second challenge of smart home systems is associated with the *system infrastructure*. The smart home system relies on sensors, actuators and other devices to collect information, which is then processed and transferred to a remote server [47]. As the sensors, actuators and other devices collect large volumes of data [48], it would require proper infrastructure, including hardware, communication protocols and computations resources within a body area network and wireless area network that facilitates delay less and seamless connectivity [49]. In the users ' homes, AI-powered edge computing could be a key enabler here, providing data, analytics, and processing power where it is most required. In addition, the infrastructure would need to consider suitable evaluation metrics such as packet loss rate, handover delay, algorithm encryption complexity and throughput to optimize the performance of the smart home system [50]. However, the infrastructure for these systems should be carefully designed to limit integration issues and loss of data. For example, using edge computing to minimize data transfer volumes) while also focusing on low maintenance and energy costs to significantly benefit the resident [49].

Finally, the third challenge includes issues with the *security and privacy* of smart home systems. Researchers in the past have demonstrated several security threat issues, including traffic analysis, eavesdropping, node compromise, denial of service (DoS), physical attack, masquerade attack, sinkhole and wormhole attacks and so on [51]. Smart home systems consist of several devices shared over an internet network [52] to ensure a continuous flow of information. This allows the attacker to remotely control the home or access private health and financial information [44]. Several organizational leaders, in the past, have taken actions to limit the impact of security and privacy issues at three levels, i.e. to anticipate and prevent cyber-threats prior to their occurrence, continuously monitoring and neutralizing any threats to the system that are currently operational and restoring regular operations as soon as a threat is detected [53]. Hence, this approach can be considered to develop efficient security and privacy mechanisms within smart homes to ensure the safety of the residents while preventing privacy violations [44].

3 Wearable Health Sensor Technologies in Smart Home Ecosystems

Wearable sensors are devices that can be worn by residents [29] and are capable of real-time physiological health monitoring such as electrocardiogram, heart rate, electromyogram, body temperature, arterial oxygen saturation, respiration rate, electrodermal activity and blood pressure. Additionally, these devices consist of micro-electro-mechanical systems (or MEMS), which measure motion and activity through accelerometers, magnetic field sensors and gyroscopes [54]. These devices, along with remote monitoring systems, have the potential to increase access to healthcare [55], reduce medical costs, minimize exposure to hospital-acquired infections [56], create new opportunities for remotely monitoring clinically relevant factors and allow individuals to actively participate in their healthcare [57]. Thus, providing a massive benefit to vulnerable populations with health issues [58].

Several studies have discussed the potential of wearable sensors in health care. Khoshmanesh et al. [56] classified these sensors into three main categories: mountable, skin-like sensors, and textile-based sensors. These three categories use different sensing mechanisms such as resistive, optical, electrochemical, bioelectrical impedance, piezothermic, triboelectric, piezoelectric, piezoresistive and capacitive to acquire the target signals [56]. The target signal is processed within the wearable and transmitted to remote monitoring devices via a low-power radio signal. Data from these devices can be collected and analysed to support disease monitoring and treatment [59]. For example, Steele et al. [60] utilized a triaxial accelerometer worn around the non-dominant arm to measure the daily physical activity of COPD patients, intending to improve physical functioning. Varatharajan et al. [61] considered analysing the continuous foot movement using a wearable motion sensor positioned around the ankle to acquire gait signals that could be used for early detection of Alzheimer's disease. Dieffenderfer et al. [62] developed a wristband, chest patch and handheld spirometer to identify environmental parameters such as ambient ozone concentration, relative humidity and temperature towards supporting asthma management. Sood, Mahajan [63] proposed a system that utilizes real-time health, location, environmental, drug and meteorological sensors to diagnose the chikungunya virus amongst infected users and take preventive measures on time. Therefore, applying wearables in smart homes can significantly improve comfort, health care and disease prevention amongst its residents [63, 64].

3.1 Architecture

The generic architecture of a wearable device can be divided into four modules, i.e. body area network, data logger, data analysis and real-time monitoring (Fig. 1). The body area network (or BAN) can be used in different wearable devices irrespective of its architecture. It requires a network of sensors being placed on the human body from

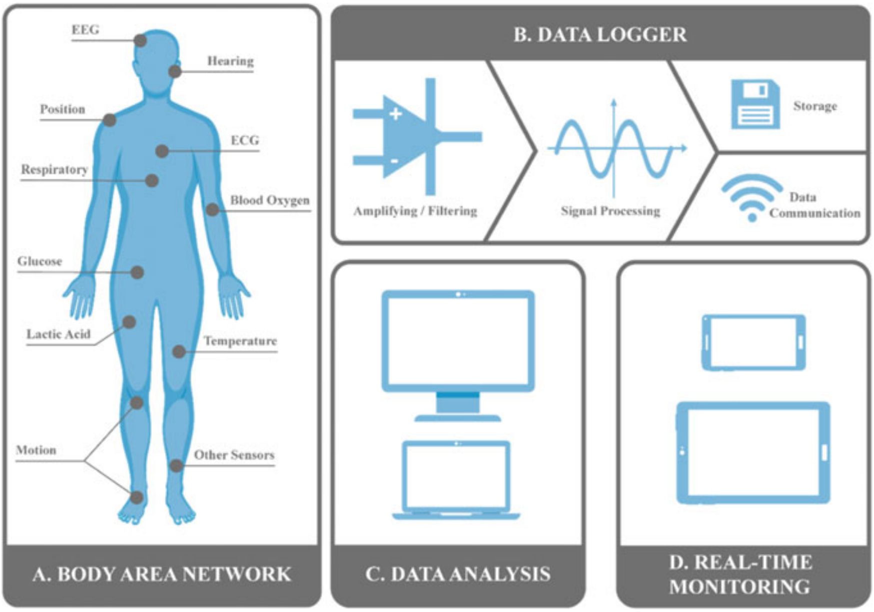

Fig. 1 Generic wearable device architecture [65]

which data is transmitted to a portable unit known as the sensing unit that processes the data extracted. This presents a clear advantage as it enables data centralisation into a single unit from different sensors to ensure remote processing. Moreover, it enhances the synchronization, control, programming and scheduling of the entire system based on the environmental and body conditions. Further, wireless communication is regarded as a key asset towards ensuring that the system is ubiquitous and mobile [65].

The data logger (or portable unit) is a user interface box that collects all the information from the sensors and other portable devices. Literature highlights two approaches to facilitate communication between the data logger and the sensors. The most simple and cheap technique is the use of wires. Some variations in this technique involve the wires woven into fabrics generally termed smart clothes to avoid loose wires and are considered favourable due to the ease of movement and increased comfort. Another approach is the use of biological channels, an innovative technique that utilizes the human body as a transmitter for electrostatic fields. The data collected through these approaches are received in the form of raw analogue data, which is amplified and converted into digital signals to be processed. The processing of data involves extracting individual features from the data to determine the subjects' health, detect disease, detect anomalies and determine support. The processed can be transmitted via a wireless network protocol or stored within an SD card [65]. Generally, the wearable relies on wireless communication standards such as Bluetooth low energy (BLE) with other devices to ensure data synchronization [66].

Wearable devices rely on several communication standards, as shown in Table 1. For example, Bluetooth is a low-power, short-range and low-cost radio frequency connectivity standard used for communication in fixed or portable devices. It operates on a 2.4 GHz spectrum with a frequency hopping technique across 79 different channels. This standard allows for up to 3 Mb/s data transmission rate over a 100 m distance. Specifically, this functions in wearable technologies using alternative protocols such as Bluetooth low energy (or BLE), an ultra-low powered technology to maximize the battery capacity, and Bluetooth 3.0 specification, which utilizes protocols similar to Wi-Fi physical (PHY) layers for increased data throughput. Another standard, arguably the most commonly used, is based on Body Area Network (or BAN), i.e. Zigbee. Zigbee is a low data-rate and low-cost standard that focus on the communication of devices with longer battery life. Zigbee operates at 868 MHz bands on a single channel, 915 MHz on 10 channels, and 2.4Ghz on 16 channels. The standard operates on a phased shift keying modulation at an offset of 250 Kb/s, with a maximum transmission range of 75 m [67]. Another popular standard adopted is Wi-Fi which allows for high data throughput of about 54–150 Mb/s between the ranges of 2.4–2.5 GHz for 35–120 m and 5.725–5.85 kHz for 70–250 m. The Wi-Fi standard focuses on providing a large bandwidth at low energy consumption, generally used when distance communication is required [65, 67]. One of the most recent standards is the IEEE 802.15.6, which focuses on a low-powered transmission with scalable rates, i.e. from 1 kb/s to over 100mb/s. This was developed for short-distance communication between 2 to 5 m and can allow up to 100 devices to connect simultaneously. This standard consists of three physical (PHY) layers distributed across a complex trans receiving hardware. The layers include ultrawideband, narrowband and human body channel [67].

Data transferred through the different wireless standards can be either stored or analysed in real-time to diagnose and predict health issues. For example, data collected from sleep sensors could be used to determine sleep issues such as sleep apnoea. A medical professional could use this data to improve the quality of care provided to the patient. In addition, the system could provide real-time monitoring and support to the patient to manage the physiological problem outside the medical environment as long as the patient has a stable internet connection [65].

4 Context-Aware and User Adaptive Smart Home Ecosystems

There is an increasing demand for healthcare technologies such as smart home ecosystems to dynamically adapt their behaviour in real-time based on user requirements, preferences, the underlying infrastructure and operational environments. Hence, several research approaches are currently being considered in developing

Table 1 Wireless technologies for wearable devices [67]

Wireless technology	Data Rate	Range	Frequency	Number of Notes	Other attributes
Bluetooth (802.15.1)	1–3 Mb/s	1–10 m	2.4–2.5 GHz	7 + 1	Small antenna, large bandwidth and crowded spectrum
BLE (802.15.1)	1 Mb/s	1–10 m	2.4–2.5 GHz	7 + 1	
ZigBee (802.15.4)	250 bb/s	10–100 m	2.4–2.5 GHz	Unlimited	
WLAN (802.11a/b/g/n)	54–150 Mb/s	35–120 m (a/b/g)	2.4–2.5 GHz	255	Small antenna, large bandwidth and severe attenuation
		70–250 m (n)	5.725–5.85 GHz		
ANT	1 Mb/s	10–30 m	2.4–2.5 GHz	N/A	
Passive RFID	868 kb/s	0–3 m	860–960 MHz	One read at a time	Large antenna, good propagation and limited bandwidth
Active RFID	10 s of Mb/s	0–100 m	433 MHz	1000 + reads at a time	Large antenna, crowded spectrum and limited bandwidth
UWB	52–480 Mb/s	3–10 m	4.2–4.8 GHz, 7.25–8.5 GHz, 3.1–10.6 GHz	127 + 1	Huge bandwidth, short-range, severe attenuation and high-rate for multimedia

systems that adapt based on individual contexts and/or requirements. The two primary approaches implemented are context-aware and self-adaptive systems [68].

A context-aware system can be defined as a software system that can understand the context of a particular system and shares its context with other systems or provide a response by itself [69]. Over the years, there have been several definitions for the context term. Most authors define the context based on location, time, identity, temperature, noise, desires, beliefs, intentions and commitments of the user [70]. For example, Brezillon [71] defined it as an interaction between humans, applications, and environments. While Brown [72] defines context as elements within a user environment that the computer knows about. Despite the numerous definitions, as highlighted by Dey [73], the most formal definition of context is "… *information that is characterized by a situation or entity, where an entity may include a person, place or object*".

Context can be classified based on instances involving different context dimensions. Prekop, Burnett [74] and Gustavsen [75] termed these dimensions as internal and external, where the internal dimensions are specified mainly by the user or captured through user interactions (i.e. user tasks, goals, processes, emotional states and work contexts), and external dimensions include context measured through hardware sensors (i.e. light, sound, movement, temperature, touch, air pressure etc.). Most context-aware systems use these dimensions to provide its user with relevant information or services [76].

Context-aware systems offer numerous different advantages that allow systems to act more autonomously to provide users with their needs and wants. In the past, context-aware systems have been implemented in healthcare to create dynamic environments to address specific research challenges using concepts such as data acquisition, interpretation, data modelling, reasoning and so on [77]. For example, Lee, Kwon [78] modelled individual contexts within a smart home environment using different ontologies including user domain, social context, home domain and function management to personalize healthcare services fully. Gómez et al. [79] proposed an Internet of Things (or IoT) monitoring system that senses the activities of older people with severe chronic conditions within their homes to enhance their quality of life. Park et al. [80] designed a context-aware simulation system that collected information from various virtual sensors and devices within the smart home domain to generate context-aware information. Neyja et al. [81] developed an IoT-based eHealth monitoring system that utilizes ECG signals to facilitate timely intervention and promote real-time monitoring of cardiovascular diseases.

Context-aware systems, in most cases, work with self-adaptive systems [82]. Self-adaptive systems have been increasingly used to manage problems related to contexts, which are subject to change over short periods and are poorly understood [83]. This is because self-adaptive systems have the potential to improve the systems by responding to issues in real-time to change context [84]; thereby improving the quality of service. Therefore, such a system enables the system to be technically and economically feasible that can provide autonomous changes to the tasks, loads, topology, and logical network characteristics [83].

Self-adaptive systems, in the past, has been conceptualized based on several different aspects, such as user requirements, environmental characteristics and system properties [85]. Salehie, Tahvildari [86] described several mechanisms adopted by self-adaptive systems to manage these aspects, including monitoring software entities and environment (i.e. context awareness), analyzing the changes, developing a plan to react to the changes and execute the plan to ensure the decisions take effect. For example, Alhafidh, Allen [87] developed a smart home system that adapts based on the stakeholders' lifestyle and anticipated activities to optimize the interface between the user and the household appliances. The system included.

i. numerous sensors to coordinate and control the smart home system to satisfy the users' behaviour,
ii. learn the behaviour of the different users and create a model to support their activity,
iii. determine the relationships between the user behaviour and heterogeneous smart nodes,
iv. manage resources to reduce wastage and maximize efficiency,
v. utilize cloud storage to store identified activities thereby enhancing long-term analysis of user behaviours,
vi. utilize agent-based systems to promote interoperability between components and sub-systems, and
vii. integrate security and privacy of user data within the system.

5 Issues in Implementation

In the past, several studies have been conducted in smart homes and context-aware systems. These studies have provided a roadmap regarding potential issues that may occur with its implementation to support the needs of the resident. These issues can be classified into four categories, which include: (i) interoperability, (ii) connectivity and (iii) context-aware architecture, (iv) security and privacy.

5.1 Interoperability

Smart homes rely on several smart nodes connected with sensors in a home area network to provide its resident with an intelligent living environment [88]. Most sensors (or devices), however, are built with different standards or communication protocols [44] that may affect their ability to ensure easy integration with a generic smart home system, which leads to the main issue of interoperability [89].

Several studies and solutions have been proposed in the past to limit issues related to interoperability. For example, Perumal et al. [90] proposed using a web-service and Simple Object Access Protocol (SOAP) framework that exchanges information and maintains operation between different smart home devices. Krishna, Verma [91] proposed the inclusion of a framework that considers several devices to communicate with one another to promote collaboration between smart devices and transfers this data to a centralized server where the smart home system can acquire, analyse, coordinate and monitor user activities. Furthermore, several leading companies are working towards achieving complete interoperability of devices that can ensure generic smart home systems development. An example of this change is evident in the Z-wave products, where Zigbee 3.0 considers interoperability with its previous versions [89].

5.2 Connectivity

Connectivity is one of the most important factors for the proper functioning of the smart home system [92]. Connectivity issues are common amongst various devices from different manufacturers and may exist because of the different standards and protocols [39]. According to Rehman et al. [93], the issues related to connectivity can be mitigated by including a unique identifier for all communication devices that allows for the development of an effective addressing policy. This would allow for the system to identify the device and ensure the quality of service. However, it may result in challenges with traffic characterization due to the inclusion of several different devices interconnected with the smart home device. To mitigate this issue, the authors discussed using a routing protocol that prevents packet loss and ensures energy efficiency, which creates an IoT system that is energy-efficient, scalable, and reliable.

5.3 Context-Aware Architecture

Context-aware computing systems utilizes heterogeneous data sources [94] to gather, process and store context data in real-time [69, 82], thereby providing services according to user needs, interaction with the environment and their localization [94]. The integration of such systems provides the user with an immersive experience that contributes to emotional, social and physical meaning throughout their daily actions and activities [94]. Hence, context-aware systems are considered a crucial part of ubiquitous or pervasive computing technologies [95]. However, when dealing with these devices, the system has to deal with different challenges. In a study by Bang, Rao [96], the authors described several issues with implementing context-aware systems. These issues include:

i. Obtaining accurate information: For the context-aware system to function efficiently, it needs to get precise information from the devices to derive future inferences. For health monitoring, information is personal and sensitive data such as vitals, schedules, contact lists, health status etc.

ii. Dealing with dynamic information: Context-aware systems function in a real-time environment that is expected to deal with dynamic information such as position, vitals, actions, emotional and physiological states, observable objects and orientations.
iii. Understand proper and relevant contexts: It is critical for context-aware systems to utilize data gathered through connected devices and hardware to provide information based on relevant contexts, addressing user requirements. Failure to support user requirements may affect system performance.
iv. Storing, Updating and Privacy of Context Information: The system would need to store data either locally or on the network. However, due to the generation of large amounts of data, there is a significant concern regarding the storage requirements and issues related to the security and privacy of user information.
v. Deciding Minimum Service that Context-Aware System should provide: The user needs are constantly changing. As a result, the system needs to consider these changes and provide contexts based on the user requirements.
vi. Handling Errors: Handling errors is critical for context-aware systems as inferences drawn must be accurate for the system to meet user requirements and ensure user security.

5.4 Security and Privacy

The smart home system is associated with connecting different devices via the internet and home shared networks [88]. In the past, researchers have highlighted several issues related to the security and privacy of smart home systems, which include aspects such as traffic analysis, eavesdropping, node compromise, denial of service (DoS), physical attack, masquerade attack, sinkhole and wormhole attacks and so on [51]. Hence, the smart home system should provide a security policy involving crypto-primitives to ensure authenticity (data does not consider malicious objects), integrity (data transmitted is identical to the data received) and confidentiality (data is inaccessible to unauthorized users) [89].

6 Conclusion

In this chapter, the concept of context-aware and user-adaptive smart home ecosystems using wearable technology is presented. Context-aware and user-adaptive systems can play a key role in developing smart home ecosystems by integrating numerous smart sensors such as wearables that can detect user activity based on different contexts. Therefore, including such a system can create a more responsive and active environment to meet user needs and requirements. As a result, several organizations worldwide are continuously looking at such practices to support monitoring and care.

The potential of context-aware and user-adaptive smart homes are threefold; (i) it can promote effective monitoring to its residents and provide improved feedback, (ii) adapt in real-time to meet the user requirements, (iii) provide at-home support to ensure changes in behaviour using wearable technologies and other devices. Moreover, in the future, with the growth and adoption of AI-powered edge computing and improved wearable hardware, it would be possible to promote better resource efficiency and thereby promote better health and behaviour outcomes.

References

1. Iversen, K., Bundgaard, H., Hasselbalch, R.B., Kristensen, J.H., Nielsen, P.B., Pries-Heje, M., et al.: Risk of COVID-19 in health-care workers in Denmark: an observational cohort study. Lancet. Infect. Dis **20**(12), 1401–1408 (2020). https://doi.org/10.1016/s1473-3099(20)30589-2
2. Ahmed, S.A.K.S., Ajisola, M., Azeem, K., Bakibinga, P., Chen, Y.-F., Choudhury, N.N., et al.: Impact of the societal response to COVID-19 on access to healthcare for non-COVID-19 health issues in slum communities of Bangladesh, Kenya, Nigeria and Pakistan: results of pre-COVID and COVID-19 lockdown stakeholder engagements. BMJ Glob. Health **5**(8), e003042 (2020). https://doi.org/10.1136/bmjgh-2020-003042
3. World Health Organization: Maintaining essential health services during the COVID-19 outbreak. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/related-health-issues (2020). Accessed 9 December 2020
4. Hirko, K.A., Kerver, J.M., Ford, S., Szafranski, C., Beckett, J., Kitchen, C., et al.: Telehealth in response to the COVID-19 pandemic: implications for rural health disparities. J. Am. Med. Inf. Assoc. JAMIA **27**(11), 1816–1818 (2020). https://doi.org/10.1093/jamia/ocaa156
5. Lobo, E.H., Abdelrazek, M., Kensing, F., Rasmussen. L.J., Livingston, P.M., Grundy, .J, et al.: Technology-based support for stroke caregiving: A rapid review of evidence. J. Nurs. Manag. n/a(n/a) (2021). https://doi.org/10.1111/jonm.13439
6. Islam, S.M., Tabassum, R.: Implementation of information and communication technologies for health in Bangladesh. Bull. World Health Organ. **93**(11), 806–809 (2015). https://doi.org/10.2471/blt.15.153684
7. Islam, S.M.S., Cartledge, S., Karmakar, C., Rawstorn, J.C., Fraser, S.F., Chow, C., et al.: Validation and acceptability of a cuffless wrist-worn wearable blood pressure monitoring device among users and health care professionals: mixed methods study. JMIR Mhealth Uhealth. **7**(10), e14706 (2019). https://doi.org/10.2196/14706
8. Islam, S.M.S., George, E.S., Maddison, R.: Effectiveness of a mobile phone text messaging intervention on dietary behaviour in patients with type 2 diabetes: a post-hoc analysis of a randomised controlled trial. Mhealth **7**, 10 (2021). https://doi.org/10.21037/mhealth-2020-3
9. Islam, S.M.S., Maddison, R.: A Comparison of blood pressure data obtained from wearable, ambulatory, and home blood pressure monitoring devices: prospective validation study. JMIR Data **1**(1), e22436 (2020). https://doi.org/10.2196/22436
10. Islam, S.M.S., Maddison, R.: Digital health approaches for cardiovascular diseases prevention and management: lessons from preliminary studies. Mhealth **7**, 41 (2021). https://doi.org/10.21037/mHealth-2020-6
11. Al-Khafajiy, M., Baker, T., Chalmers, C., Asim, M., Kolivand, H., Fahim, M., et al.: Remote health monitoring of elderly through wearable sensors. Multim. Tools Appl. **78**(17), 24681–24706 (2019). https://doi.org/10.1007/s11042-018-7134-7
12. Whitelaw, S., Mamas, M.A., Topol, E., Van Spall, H.G.C.: Applications of digital technology in COVID-19 pandemic planning and response. Lancet Digital Health **2**(8), e435–e440 (2020). https://doi.org/10.1016/s2589-7500(20)30142-4

13. Ting, D.S.W., Carin, L., Dzau, V., Wong, T.Y.: Digital technology and COVID-19. Nat. Med. **26**(4), 459–461 (2020). https://doi.org/10.1038/s41591-020-0824-5
14. Drew, D.A., Nguyen, L.H., Steves, C.J., Menni, C., Freydin, M., Varsavsky, T., et al.: Rapid implementation of mobile technology for real-time epidemiology of COVID-19. Science **368**(6497), 1362–1367 (2020). https://doi.org/10.1126/science.abc0473
15. Torous, J., Jän Myrick, K., Rauseo-Ricupero, N., Firth, J.: Digital mental health and COVID-19: using technology today to accelerate the curve on access and quality tomorrow. JMIR Ment. Health **7**(3), e18848 (2020). https://doi.org/10.2196/18848
16. George, G., Lakhani, K.R., Puranam, P.: What has changed? The impact of covid pandemic on the technology and innovation management research agenda. J. Manag. Stud. **57**(8), 1754–1758 (2020). https://doi.org/10.1111/joms.12634
17. Figueroa, C.A., Aguilera, A.: The need for a mental health technology revolution in the COVID-19 pandemic. Front. Psychiatry. **11**, 523 (2020). https://doi.org/10.3389/fpsyt.2020.00523
18. World Health Organization: Current and future long-term care needs. https://www.who.int/chp/knowledge/publications/ltc_needs.pdf (2002). Accessed 9 December 2020
19. Choi, D., Choi, H., Shon, D.: Future changes to smart home based on AAL healthcare service. J. Asian Archit. Build. Eng. **18**(3), 190–199 (2019). https://doi.org/10.1080/13467581.2019.1617718
20. Morris, M.E., Adair, B., Miller, K., Ozanne, E., Hansen, R., Pearce, A.J., et al.: Smart-home technologies to assist older people to live well at home. J. Aging Sci. **1**(1), 1–9 (2013). https://doi.org/10.4172/jasc.1000101
21. Vlachostergiou, A., Stratogiannis, G., Caridakis, G., Siolas, G., Mylonas, P.: User adaptive and context-aware smart home using pervasive and semantic technologies. J. Electr. Comput. Eng. **2016**, 4789803 (2016). https://doi.org/10.1155/2016/4789803
22. Yu, J., An, N., Hassan, T., Kong, Q.: A pilot study on a smart home for elders based on continuous in-home unobtrusive monitoring technology. HERD: Health Environ. Res. Design J. **12**(3), 206–219 (2019). https://doi.org/10.1177/1937586719826059
23. Mocrii, D., Chen, Y., Musilek, P.: IoT-based smart homes: a review of system architecture, software, communications, privacy and security. Internet of Things **1–2**, 81–98 (2018). https://doi.org/10.1016/j.iot.2018.08.009
24. Bianchi, V., Bassoli, M., Lombardo, G., Fornacciari, P., Mordonini, M., Munari, I.D.: IoT wearable sensor and deep learning: an integrated approach for personalized human activity recognition in a smart home environment. IEEE Internet Things J. **6**(5), 8553–8562 (2019). https://doi.org/10.1109/JIOT.2019.2920283
25. Wang, L., Gu, T., Tao, X., Chen, H., Lu, J.: Recognizing multi-user activities using wearable sensors in a smart home. Pervasive Mob. Comput. **7**(3), 287–298 (2011). https://doi.org/10.1016/j.pmcj.2010.11.008
26. Reeder, B., Chung, J., Lyden, K., Winters, J., Jankowski, C.M.: Older women's perceptions of wearable and smart home activity sensors. Inform. Health Soc. Care **45**(1), 96–109 (2020). https://doi.org/10.1080/17538157.2019.1582054
27. Yang, H., Lee, W., Lee, H.: IoT smart home adoption: the importance of proper level automation. J. Sensors **2018**, 6464036 (2018). https://doi.org/10.1155/2018/6464036
28. Kim, M.J., Cho, M.E., Jun, H.J.: Developing design solutions for smart homes through user-centered scenarios. Front. Psychol. **11**, 335 (2020). https://doi.org/10.3389/fpsyg.2020.00335
29. Amirhosein, G., Ali, G., John, T., Hossein, O., Anthony, F., Nicola, N., et al.: The essence of smart homes: application of intelligent technologies towards smarter urban future. In: Information Resources Management A, editor. Artificial Intelligence: Concepts, Methodologies, Tools, and Applications. Hershey, PA, USA: IGI Global, pp. 79–121 (2017)
30. De Silva, L.C., Morikawa, C., Petra, I.M.: State of the art of smart homes. Eng. Appl. Artif. Intell. **25**(7), 1313–1321 (2012). https://doi.org/10.1016/j.engappai.2012.05.002
31. Arcelus, A., Jones, M.H., Goubran, R., Knoefel, F.: Integration of smart home technologies in a health monitoring system for the elderly. In: 21st International Conference on Advanced Information Networking and Applications Workshops (AINAW'07), pp. 820–825 (2007)

32. Chen, C., Pomalaza-Raez, C.: Design and evaluation of a wireless body sensor system for smart home health monitoring. In: GLOBECOM 2009 - 2009 IEEE Global Telecommunications Conference, pp. 1–6 (2009)
33. Pham, M., Mengistu, Y., Do, H., Sheng, W.: Delivering home healthcare through a cloud-based smart home environment (CoSHE). Futur. Gener. Comput. Syst. **81**, 129–140 (2018). https://doi.org/10.1016/j.future.2017.10.040
34. Jung, Y.: Hybrid-aware model for senior wellness service in smart home. Sensors **17**(5) (2017). https://doi.org/10.3390/s17051182
35. Giovani Rubert, L., Leandro Oliveira, F., Ederson, B., Cicero, R., Samuel, V.: Definition of a pervasive architecture for a central monitoring of homecare systems. In: Dimitrios, I.F. (ed.) Handbook of Research on Trends in the Diagnosis and Treatment of Chronic Conditions, pp. 412–423. IGI Global, Hershey, PA, USA (2016)
36. Freitas, L.O., Pereira, R.T., Pereira, H.G.G., Martini, R.G., Mozzaquatro, B., Kasper, J., et al.: A Methodology for an architecture of pervasive systems to homecare environments. Procedia Technol. **5**, 820–829 (2012). https://doi.org/10.1016/j.protcy.2012.09.091
37. Li, K.F.: Smart home technology for telemedicine and emergency management. J. Ambient. Intell. Humaniz. Comput. **4**(5), 535–546 (2013). https://doi.org/10.1007/s12652-012-0129-8
38. Suresh, S., Sruthi, P.V.: A review on smart home technology. In: 2015 Online International Conference on Green Engineering and Technologies (IC-GET), pp. 1–3 (2015)
39. Alaa, M., Zaidan, A.A., Zaidan, B.B., Talal, M., Kiah, M.L.M.: A review of smart home applications based on Internet of Things. J. Netw. Comput. Appl. **97**, 48–65 (2017). https://doi.org/10.1016/j.jnca.2017.08.017
40. Marikyan, D., Papagiannidis, S., Alamanos, E.: A systematic review of the smart home literature: a user perspective. Technol. Forecast. Soc. Chang. **138**, 139–154 (2019). https://doi.org/10.1016/j.techfore.2018.08.015
41. Kelly, D.: CARE AT HOME-Smart support at home: the integration of telecare technology with primary and community care systems-David Kelly reports on progress by the sixth year of West Lothian's use of IT. Br. J. Healthc. Comput. Inf. Manag. **22**(3), 19–21 (2005)
42. Skubic, M., Alexander, G., Popescu, M., Rantz, M., Keller, J.: A smart home application to eldercare: current status and lessons learned. Technol. Health Care **17**(3), 183–201 (2009). https://doi.org/10.3233/THC-2009-0551
43. Tomita, M.R., Mann, W.C., Stanton, K., Tomita, A.D., Sundar, V.: Use of currently available smart home technology by Frail Elders: process and outcomes. Top. Geriat. Rehab. **23**(1) (2007)
44. Almusaylim, Z.A., Zaman, N.: A review on smart home present state and challenges: linked to context-awareness internet of things (IoT). Wirel. Netw. **25**(6), 3193–3204 (2019). https://doi.org/10.1007/s11276-018-1712-5
45. Perumal, T., Ramli, A.R., Leong, C.Y., Mansor, S., Samsudin, KJIJoSH.: Interoperability for smart home environment using web services. **2**(4), 1–16 (2008)
46. Islam, S.M.S., Khosravi, A.: The need for a prediction model assessment framework. Lancet Global Health **9**(4), e404 (2021). https://doi.org/10.1016/s2214-109x(21)00022-x
47. Domb, M.: Smart home systems based on internet of things. In: Ismail, Y. (ed.) Internet of Things (IoT) for Automated and Smart Applications, pp. 25–38. IntechOpen, London, UK (2019)
48. Sethi, P., Sarangi, S.R.: Internet of things: architectures, protocols, and applications. J. Electr. Comput. Eng. **2017**, 9324035 (2017). https://doi.org/10.1155/2017/9324035
49. Majumder, S., Aghayi, E., Noferesti, M., Memarzadeh-Tehran, H., Mondal, T., Pang. Z., et al.: Smart homes for elderly healthcare—Recent advances and research challenges. Sensors **17**(11) (2017). https://doi.org/10.3390/s17112496
50. Talal, M., Zaidan, A.A., Zaidan, B.B., Albahri, A.S., Alamoodi, A.H., Albahri, O.S., et al.: Smart home-based iot for real-time and secure remote health monitoring of triage and priority system using body sensors: multi-driven systematic review. J. Med. Syst. **43**(3), 42 (2019). https://doi.org/10.1007/s10916-019-1158-z
51. Mouaatamid, O.E.l., Lahmer, M., Belkasmi, M.: Internet of Things Security: Layered classification of attacks and possible Countermeasures. La sécurité de l'Internet des objets : classification en couches des attaques et contre-mesures possibles. (9), 66–80 (2016)

52. Batalla, J.M., Gonciarz, F.: Deployment of smart home management system at the edge: mechanisms and protocols. Neural Comput. Appl. **31**(5), 1301–1315 (2019). https://doi.org/10.1007/s00521-018-3545-7
53. D'Mello, O., Gelin, M., Khelil, F.B., Surek, R.E., Chi, H.: Wearable IoT security and privacy: a review from technology and policy perspective. In: Doss, R., Piramuthu, S., Zhou, W. (eds.) Future Network Systems and Security, pp. 162–177. Springer International Publishing, Cham (2018)
54. Majumder, S., Mondal, T., Deen, M.J.: Wearable sensors for remote health monitoring. sensors. **17**(1) (2017). https://doi.org/10.3390/s17010130
55. Patel, S., Park, H., Bonato, P., Chan, L., Rodgers, M.: A review of wearable sensors and systems with application in rehabilitation. J. Neuroeng. Rehabil. **9**(1), 21 (2012). https://doi.org/10.1186/1743-0003-9-21
56. Khoshmanesh, F., Thurgood, P., Pirogova, E., Nahavandi, S., Baratchi, S.: Wearable sensors: at the frontier of personalised health monitoring, smart prosthetics and assistive technologies. Biosens. Bioelectron. **176**, 112946 (2021). https://doi.org/10.1016/j.bios.2020.112946
57. Appelboom, G., Camacho, E., Abraham, M.E., Bruce, S.S., Dumont, E.L.P., Zacharia, B.E., et al.: Smart wearable body sensors for patient self-assessment and monitoring. Archiv. Public Health **72**(1), 28 (2014). https://doi.org/10.1186/2049-3258-72-28
58. Mageroski, A., Alsadoon, A., Prasad, P.W.C., Pham, L., Elchouemi, A.: Impact of wireless communications technologies on elder people healthcare: smart home in Australia. In: 2016 13th International Joint Conference on Computer Science and Software Engineering (JCSSE), pp. 1–6 (2016)
59. Rodgers, M.M., Pai, V.M., Conroy, R.S.: Recent advances in wearable sensors for health monitoring. IEEE Sens. J. **15**(6), 3119–3126 (2015). https://doi.org/10.1109/JSEN.2014.2357257
60. Steele, B.G., Holt, L., Belza, B., Ferris, S., Lakshminaryan, S., Buchner, D.M.: Quantitating physical activity in COPD using a triaxial accelerometer. Chest **117**(5), 1359–1367 (2000). https://doi.org/10.1378/chest.117.5.1359
61. Varatharajan, R., Manogaran, G., Priyan, M.K., Sundarasekar, R.: Wearable sensor devices for early detection of Alzheimer disease using dynamic time warping algorithm. Clust. Comput. **21**(1), 681–690 (2018). https://doi.org/10.1007/s10586-017-0977-2
62. Dieffenderfer, J., Goodell, H., Mills, S., McKnight, M., Yao, S., Lin, F., et al.: Low-power wearable systems for continuous monitoring of environment and health for chronic respiratory disease. IEEE J. Biomed. Health Inf. **20**(5), 1251–1264 (2016). https://doi.org/10.1109/JBHI.2016.2573286
63. Sood, S.K., Mahajan, I.: Wearable IoT sensor based healthcare system for identifying and controlling chikungunya virus. Comput. Ind. **91**, 33–44 (2017). https://doi.org/10.1016/j.compind.2017.05.006
64. Maddison, R., Rawstorn, J.C., Shariful Islam, S.M., Ball, K., Tighe, S., Gant, N., et al.: mHealth interventions for exercise and risk factor modification in cardiovascular disease. Exerc. Sport Sci. Rev. **47**(2), 86–90 (2019). https://doi.org/10.1249/JES.0000000000000185
65. Dias, D., Paulo Silva Cunha, J.: Wearable health devices—Vital sign monitoring, systems and technologies. Sensors **18**(8) (2018). https://doi.org/10.3390/s18082414
66. Cusack, B., Antony, B., Ward, G., Mody, S.: Assessment of security vulnerabilities in wearable devices. In: Valli, C., (ed.) The Proceedings of 15th Australian Information Security Management Conference. Perth, Western Australia: Edith Cowan University, Perth, Western Australia, pp. 42–48 (2017)
67. Soh, P.J., Vandenbosch, G.A.E., Mercuri, M., Schreurs, D.M.M.: Wearable wireless health monitoring: current developments, challenges, and future trends. IEEE Microw. Mag. **16**(4), 55–70 (2015). https://doi.org/10.1109/MMM.2015.2394021
68. Hussein, M., Han, J., Colman, A., Yu, J.: An architecture-based approach to developing context-aware adaptive systems. In: 2012 IEEE 19th International Conference and Workshops on Engineering of Computer-Based Systems, pp. 154–163 (2012)

69. Millham, R.: Context-aware systems: a more appropriate response system to hurricanes and other natural disasters. Procedia Comput. Sci. **36**, 21–26 (2014). https://doi.org/10.1016/j.procs.2014.09.039
70. Zimmermann, A., Lorenz, A., Oppermann. R.: An operational definition of context. In: Kokinov, B., Richardson, D.C., Roth-Berghofer, T.R., Vieu, L. (eds.) Modeling and Using Context. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 558–571 (2007)
71. Brezillon, P.: Focusing on context in human-centered computing. IEEE Intell. Syst. **18**(3), 62–66 (2003). https://doi.org/10.1109/MIS.2003.1200731
72. Brown, P.J.: The stick-e document: a framework for creating context-aware applications. Electron. Publ. **8**, 259–272 (1995)
73. Dey, A.K.: Understanding and using context. Pers. Ubiquit. Comput. **5**(1), 4–7 (2001). https://doi.org/10.1007/s007790170019
74. Prekop, P., Burnett, M.: Activities, context and ubiquitous computing. Comput. Commun. **26**(11), 1168–1176 (2003). https://doi.org/10.1016/S0140-3664(02)00251-7
75. Gustavsen, R.M.: Condor–an application framework for mobility-based context-aware applications. In: Proceedings of the Workshop on Concepts and Models for Ubiquitous Computing (2002)
76. Abowd, G.D., Dey, A.K., Brown, P.J., Davies, N., Smith, M., Steggles, P.: Towards a better understanding of context and context-awareness. In: Gellersen, H.-W. (ed.) Handheld and Ubiquitous Computing. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 304–307 (1999)
77. Sridevi, S., Sayantani, B., Amutha, K.P., Mohan, C.M., Pitchiah, R.: Context aware health monitoring system. In: Zhang, D., Sonka, M. (eds.) Medical Biometrics. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 249–257 (2010)
78. Lee, H., Kwon, J.: Ontology model-based situation and socially-aware health care service in a smart home environment. Int. J. Smart Home **7**(5), 239–250 (2013). https://doi.org/10.14257/ijsh.2013.7.5.24
79. Gómez, J., Oviedo, B., Zhuma, E.: Patient monitoring system based on internet of things. Procedia Comput. Sci. **83**, 90–97 (2016). https://doi.org/10.1016/j.procs.2016.04.103
80. Park, J., Moon, M., Hwang, S., Yeom, K.: CASS: a context-aware simulation system for smart home. In: 5th ACIS International Conference on Software Engineering Research, Management & Applications (SERA 2007), pp. 461–467 (2007)
81. Neyja, M., Mumtaz, S., Huq, K.M.S., Busari, S.A., Rodriguez, J., Zhou, Z.: An IoT-based e-health monitoring system using ECG signal. In: GLOBECOM 2017—2017 IEEE Global Communications Conference, pp. 1–6 (2017)
82. Geihs, K., Wagner, M.: Context-awareness for self-adaptive applications in ubiquitous computing environments. In: Vinh, P.C., Hung, N.M., Tung, N.T., Suzuki, J. (eds.) Context-aware systems and applications. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 108–120 (2013)
83. Sawyer, P., Bencomo, N., Whittle, J., Letier, E., Finkelstein, A.: Requirements-aware systems: a research agenda for RE for self-adaptive systems. In: 2010 18th IEEE International Requirements Engineering Conference, pp. 95–103 (2010)
84. Sabatucci, L., Seidita, V., Cossentino, M.: The four types of self-adaptive systems: a metamodel. In: De Pietro, G., Gallo, L., Howlett, R.J., Jain, L.C. (eds.) Intelligent Interactive Multimedia Systems and Services 2017, pp. 440–450. Springer International Publishing, Cham (2018)
85. Naqvi, M.: Claims and supporting evidence for self-adaptive systems–A literature review. http://lnu.diva-portal.org/smash/record.jsf?pid=diva2%3A512439&dswid=7172 (2012). Accessed 7 September 2021
86. Salehie, M., Tahvildari, L.: Towards a goal-driven approach to action selection in self-adaptive software. Software: Pract. Exp. **42**(2), 211–233 (2012). https://doi.org/10.1002/spe.1066
87. Alhafidh, B., Allen, W.: Design and simulation of a smart home managed by an intelligent self-adaptive system. Int. J. Eng. Res. Appl. **6**(8), 64–90 (2016)
88. Samuel, S.S.I.: A review of connectivity challenges in IoT-smart home. In: 2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC). Muscat, Oman: IEEE, pp. 1–4 (2016)

89. Risteska Stojkoska, B.L., Trivodaliev, K.V.: A review of Internet of Things for smart home: challenges and solutions. J. Clean. Prod. **140**, 1454–1464 (2017). https://doi.org/10.1016/j.jclepro.2016.10.006
90. Perumal, T., Ramli, A.R., Leong, C.Y.: Interoperability framework for smart home systems. IEEE Trans. Consum. Electron. **57**(4), 1607–1611 (2011). https://doi.org/10.1109/TCE.2011.6131132
91. Krishna, M.B., Verma, A.: A framework of smart homes connected devices using Internet of Things. In: 2016 2nd International Conference on Contemporary Computing and Informatics (IC3I), pp. 810–815 (2016)
92. Cho, J.Y., Lee, H.S., Lee, B.G.: Connectivity issues on IoT business-the Korean case of smart home network. In: The Second International Conference on Electrical, Electronics, Computer Engineering and their Applications (EECEA2015), p. 120 (2015)
93. Rehman, H.U., Asif, M., Ahmad, M.: Future applications and research challenges of IOT. In: 2017 International Conference on Information and Communication Technologies (ICICT), pp. 68–74 (2017)
94. Muñoz-Benítez, J., Molero-Castillo, G., Benítez-Guerrero, E.: Chapter 2—Data fusion architecture of heterogeneous sources obtained from a smart desk. In: Wister, M., Pancardo, P., Acosta, F., Hernández, J.A. (eds.) Intelligent Data Sensing and Processing for Health and Well-Being Applications, pp. 23–40. Academic Press (2018)
95. Hong, J.-y., Suh, E.-h., Kim, S.-J.: Context-aware systems: A literature review and classification. Expert Syst. Appl. **36**(4), 8509–8522 (2009). https://doi.org/10.1016/j.eswa.2008.10.071
96. Bang, A.O., Rao, U.P.: Context-aware computing for IoT: history, applications and research challenges. In: Goyal, D., Chaturvedi, P., Nagar, A.K., Purohit, S.D. (eds.) Proceedings of Second International Conference on Smart Energy and Communication. Singapore: Springer Singapore, pp. 719–726 (2021)

Wearable Tracking: An Effective Smartwatch Approach in Distributed Population Tracking During Pandemics

Gurdeep Singh, Robin Doss, and Sasan Adibi

Abstract The recent trend among diverse groups and industries is towards adopting smart devices, comprising smart watches (wearable and miniature smart gadgets). These intelligent objects can serve as economical gadgets capable of regularly observing individuals and patients with various health-related ailments. This chapter highlights a generalised approach for designing and developing wearable internet of things (wIoT) with enabled health technology solutions. These solutions can act as predictive and real-time mechanisms to issue alarms and execute notifications, enhance context-aware location features, and promote contact tracing of the subject to respond with early management procedures. Big data generated, by these devices can also be used for semantic analysis, generating and examining predictive health analytic insights and developing artificial intelligence applications that utilise machine learning methodologies. We cover motivational factors for developing wIoT solutions, their relationship and the role of ambient intelligence and the internet of things to serve diverse healthcare scenarios, such as self-health and home-based care. We also discuss the methodology for wIoT solution applicability, reviewing some of their benefits during pandemics and the underlying challenges concerning security and privacy issues regarding robust design and the development and implementation of health technology systems that serve distributed populations during pandemics, including COVID-19.

Keywords Wearable IoT System · Context-aware location · Semantic analysis · Machine learning in Healthcare · Self-care Technology · Smartwatch applicability

1 Introduction

Over the past decade of the expansion of the internet of things (IoT) platform, its widespread implementation has enhanced its computing capabilities to also address

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healthcare needs. It has guided emerging ambient assisted living (AAL) technologies, associated systems, solutions, and ubiquitous technologies. It has extended its presence in smart monitoring, e-health, and other healthcare applications to observe, regularly monitor, and update the patient or resident's condition and health in a real-time environment. Potentially these intelligent or AAL concepts can be used to diagnose, prevent, cure, or improve the health-associated needs of the aged or those most in need [26], 579–590.

Moreover, IoT-related paradigms of wearable devices and the internet of medical things with pervasive capabilities have efficiently provided a new dimension to modern computing technologies to serve the healthcare industry. AAL includes complex systems such as smart home environments, robotics, other intelligent monitoring, and detection systems with multiple functionalities [7], 78, [15], 74–92, [33], 17. In addition, ambient solutions including RFID tags, wearable, and smartwatch solutions can be attributed to assisted living having revamped procedures that can handle healthcare needs and responses for patients, medical personnel, and other associated staff. e-health or mobile health applications used within a real-time environment to support daily living have contributed economically and widely to better healthcare promotion and practices. Furthermore, the evolution of wearable devices with wireless communication capabilities, wireless sensor networks (WSNs) and body area networks (BANs) have grown rapidly and has been adopted in a variety of industry sectors. The healthcare industry has widely implemented these technologies for elderly care, promoting daily living activities, chronic disease management, cognitive care, and monitoring patients in emergency care through smart environments [21], 1947–1960, [4], 719–724. However, the use of these solutions, in addition to the integration of multiple technologies, can be successfully implemented for monitoring a population during pandemics ranging from different healthcare scenarios such as self-health or home care to aged care centres, effectively securing vulnerable population groups, frontline staff and other health and related stakeholders.

2 Background

There are many prevalent AAL technologies in healthcare and, potentially, smartwatches or wearable IoT solutions for populations or patients during pandemics such as COVID can be presented on specific grounds. Firstly, we present some facts that co-relate and establish the reasons for the AAL development of these solutions for healthcare centres and self-health management. Some questions require attention, highlighting the need to explore and successfully implement ambient solutions to address future healthcare facts and requirements [13].

2.1 Facts & Figures

In this section, some of the statistics suggest the social demographics and health trends among future populations. Moreover, these statistics can highlight the potential for developing IoT solutions aimed at specific health targets and disorders.

(1) Ageing population: This represents an alarming global concern e.g. approximately 20% of the population will be 60 years or older by 2050 [26], 579–590.

(2) Health trends: In the USA, the ageing population projection by 2030 stands at 70.3 million and 18.6 million people over the age of 65–80, respectively. The current incidence rates anticipate nearly 2 million new cases of congestive heart failure annually among people over 65 by 2030. Congestive heart failure is a costly medical illness involving a $40 billion annual expenditure comprising 5.4% of the healthcare budget. The societal impact of this expanding epidemic in the next 30 years is truly alarming [27], M88–M96.

(3) People living in isolation: In the study [28], 16–20, almost 50% of patients with heart failure reported social isolation, which is strongly associated with heart failure rehospitalisation. Further [22], 80–83 have investigated the time lapse between death and discovery. Older people living in isolation are not easily monitored or assisted in critical situations, and some are only discovered after death.

2.2 Pandemic-Related Health Targets

This section covers health targets that can potentially impact populations with direct and indirect outcomes of infection and disease. We have covered studies concerning cardiac disorders with routine or underlying issues. Moreover, the impact of pandemic-related infections is highlighted with direct or indirect outcomes, specifically covering studies associated with COVID-19.

2.2.1 COVID-19

The COVID-19 pandemic has led to increased fatality and concern for people suffering with cardiovascular disorders. Moreover, acute cardiac injury and abnormality directly impact 8–12% of patients with COVID-19. This can therefore increase myocardial injury and systemic inflammation as a result of underlying cardiovascular disorders or impacts during the course outcome of the COVID infection [9], 247–250. However [10], 1439–1444 have evaluated the risks related to cardiac arrest and arrhythmias and their relationship towards mortality and conclude that it is a consequence of systemic illness rather than from the direct effects of COVID-19.

Many of the cases during the COVID-19 pandemic involve cardiovascular failure or deaths related to cardiovascular failure, which can be heart attacks or strokes [8]. Wadhera et al. [31], 159–169 refer to an increase in deaths due to heart and related hypertensive diseases during the onset of the COVID-19 pandemic in the United States. The presented findings explain the indirect cause of death of patients with cardiovascular disease. Banerjee et al. [8] investigates cardiovascular diseases that have an increased mortality risk through COVID-19, along with the impact or reduced supply and demand for cardiovascular-related disease services that can reduce the mortality rate during and after the pandemic. Some specific cardiac disorders and definitions are covered in the next section.

2.2.2 Cardiac Disorders

Apart from the common health disorders, heart rate disparities range across many diseases. Some of the specific health-related disorders targeted by IoT solutions are highlighted in this section. In many cardiac-related disorders, monitoring functional heart parameters is very important for appropriately diagnosing health-related conditions. Further, detecting irregularities, timely diagnosis, and health advice provision can add value to health services and promote wellbeing. Health disorders or targets are covered as follows:

(1) Cardiac or heart arrhythmias: Lack of coordination of electrical impulses causes an irregular heart rate. Heart arrhythmias can be a life-threatening condition and can lead to stroke and heart failure. They comprises tachycardia and bradycardia, which are fast and slow heart rate conditions, respectively.[1]

(2) Cardiac asthma: Heart rate beats per minute (bpm) is an essential underlying factor in this condition, and increased heart rate and blood pressure are some of the main signs and symptoms of cardiac asthma.[2] To support the argument, the [32], 942–946 study explored cardiac arrhythmias in adult patients to determine the asthma risk associated with cardiac arrhythmias and electrocardiographic characteristics. It concluded that adult patients with asthma more commonly presented with tachycardia and premature ventricular contractions on ECG than non-asthmatic patients. In [24], 6–10, heart rate as a risk factor for cardiovascular disease presented the risk associated with an increased heart rate was comparable to the observed risk with high blood pressure. Therefore, an increase in 10 heartbeats per minute is associated with a 20% increase in cardiac deaths.

(3) Stroke: Stroke is another condition whereby the blood supply to the brain is interrupted. An irregular pulse and high blood pressure are underlying factors that can be managed to prevent stroke. Another critical feature with this condition is a timely response or emergency assistance.[3]

[1] https://www.mayoclinic.org/diseases-conditions/heart-arrhythmia/symptoms-causes/syc-20350668.

[2] https://www.mydr.com.au/asthma/bronchial-asthma-and-cardiac-asthma.

[3] https://strokefoundation.org.au/en/About-Stroke/Prevent-Stroke.

2.3 Ambient Intelligence

Ambient intelligence is an information technology paradigm with the capability to equip or empower populations with digital environments that are adaptive, sensitive, and responsive to human needs [14], 344–352. Proposed in [17], 804–809, the AAL paradigm can be established through IoT combined with pervasive technology or smart objects serving as a communication channel among different stakeholders for closed-loop healthcare services. Thus AAL is the IoT platform powered by artificial intelligence to address ageing and health compromised people's healthcare needs. Ambient intelligence technology leads to IoT, which also has a strong relationship with AAL [17], 804–809, [20], 678–708.

2.4 Internet of Things

IoT [5], 2787–2805 is a novel paradigm in which various things and objects interact and cooperate with neighbours through unique addressing schemes to reach a common goal, including RFID tags, sensors, smart devices and mobile phones. Atzori et al. [5], 2787–2805 presented IoT-oriented visions for things, the internet and semantic applications. We have identified a service-oriented vision towards real-time monitoring and semantic analysis among diverse industries, businesses, and user-specific domains related to service customisation preferences and relative use (Fig. 1).

IoT has diversified m-health platforms to deliver real-time services beyond urban or controlled healthcare environments. IoT platforms, combined with ambient intelligence, can implement imperative healthcare solutions and promote health services on a large scale.

3 Healthcare Scenarios

Do different healthcare settings describe how IoT solutions can be efficiently applied to different healthcare settings to fulfil imperative requirements such as monitoring devices? We cover the self-health use case study to portray the effectiveness of wearable or pervasive computing methodology and its contribution to control the transmission of infection during pandemics such as COVID-19.

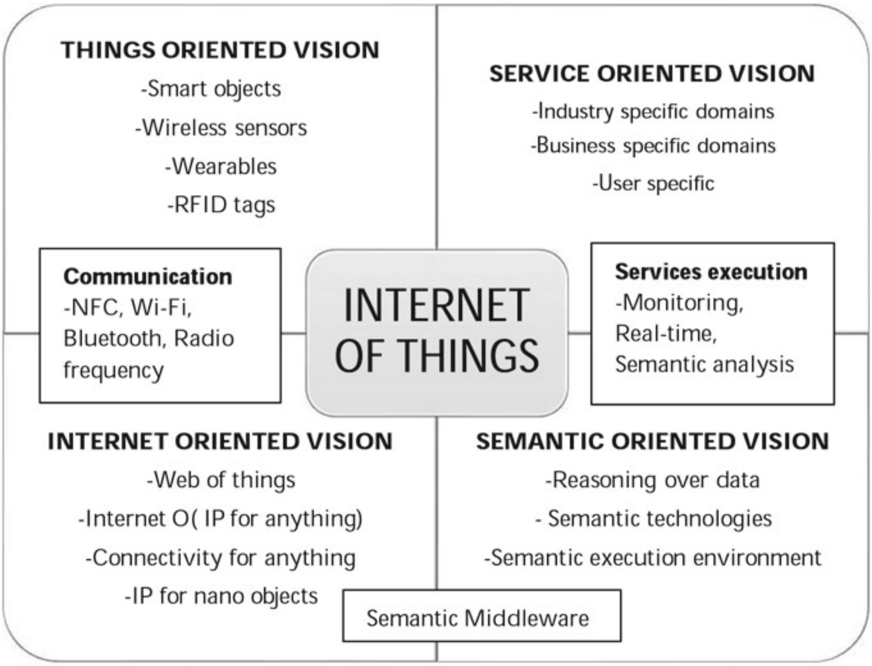

Fig. 1 Atzori et al. [5], 2787–2805 presents an IoT-oriented vision involving components, interaction, integration, and communication within the network to support ambient solutions for pervasive implementation or smart monitoring. We have provided a new service-oriented vision and service execution in addition to previous IoT-oriented visions

3.1 Self-Health Care and Home-Based Care

This is another recent trend that originated in the healthcare sector. Patients are indicating an increasing preference to practise self-health or home-based care instead of entering aged care homes or other smart homes or rehabilitation facilities. Even the elderly prefer home-based care. Some of the reasons attributed to this can be the high admission costs and difficulty in adjusting to the environment. Moreover, many non-elderly patients suffering from cardiovascular disorders, asthmatic conditions and obesity problems prefer self-health care rather than regularly visiting a clinical setting, and a similar situation applies to people living in rural communities. Perhaps around-the-clock observations of people or patients specifically for physiological monitoring, including for heart rate disparities, can be achieved through wearable smartwatches in real-time, along with detailed interaction-related activities undertaken at any given time of the day. Thus an everyday record of health-related data can be stored for future predictive diagnoses and directions. wIoT solutions can effectively promote self-health management, around the clock or for constant observation and can respond in a timely manner in an emergency, even for groups of patients. Other reasons, such as the associated cost of expensive monitoring systems, the service cost of doctors attending to patients when needed and patients isolation needs can be taken care of to prevent the further spread of infection during communicable disease pandemics. Every step or precautionary step can be planned ahead of time, along with context-aware locations or detection services.

3.2 Methodology and Solution Applicability

This section will cover the study's methodology, which includes the relevance of wearable IoT, smartwatch or pervasive device applicability for specific causes in more detail, including semantic analysis, activity tracking and context-aware location services to support implementation during pandemics.

3.2.1 Solution Applicability

Aced López [1], 133–144 anticipate a user study to support hospital caregivers and healthcare staff. Corno et al. [14], 344–352 present an appropriate solution for assisted living facilities (ALFs—a system to support the routine activities of healthcare staff working with disadvantaged inmates of ALFs with cognitive or physical impairments.

We have devised the usage and application of wIoT solutions within diverse scenarios with integrated adoption and applications in distributed networks. These solutions can involve smartwatches as an integral component in order to observe physiological parameters and the activity tracking of individuals in real-time. Machine learning enabled applications can monitor and respond effectively with automated responses on configured and adaptive thresholds. In addition, the enhanced features of machine learning embedded applications can also promote notifications, alarms and context aware location inputs for the subject or individual in real-time. These solutions or applications can also be used to undertake semantic analysis on data generated via these platforms with certain user-specific domains or requirements to observe and develop health insights for future analysis and wellbeing. This approach to health technology systems can be effective for populations during pandemics such as COVID-19 for advanced and enhanced health observation and promotion.

3.2.2 Semantic Analysis of the Data or System

This is an important aspect and will present a considerable contribution whereby machine learning and artificial intelligence methods or applications undertake a lead role in solving and providing real-time solutions. However, constructive results are drawn based on data gathered, generated, and analysed. To present an example, consider the Fitbit smartwatch that can generate a large amount of data that includes

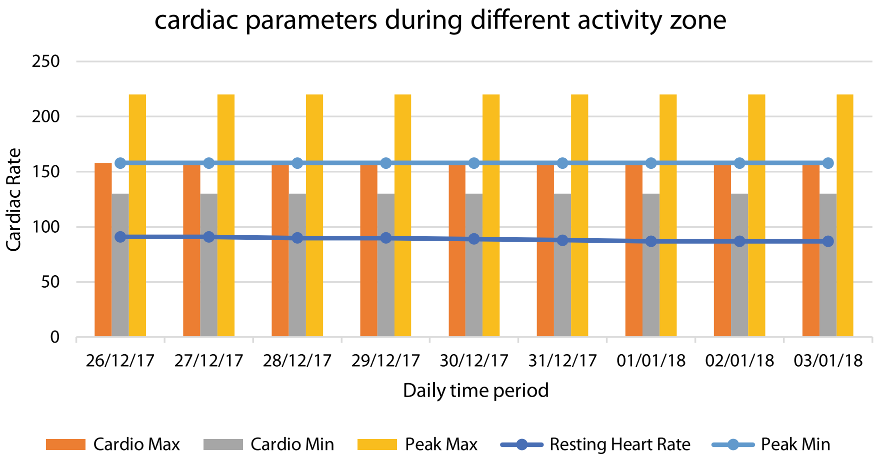

Fig. 2 Cardiac parameters during different activity zones, presenting cardio maximum, cardio minimum, peak maximum, peak minimum, and resting heart rate. The above scenario validates the different activity zones and heart rate bpm parameters. User data adopted through the Fitbit smartwatch is presented for activity and heart rate parameters

BMI, food logs, water intake or hydration, activity recognition, exercise goals and heart rate zones. Such data collection, experimentation and the resulting analysis can lead the way to improve the health and wellbeing of the wider community. It can raise red flags or monitor activities or the derailment of wellbeing among the wider population on a broader scale. Moreover, as highlighted earlier, considering all the categories or user inputs, it can promote real-time solutions and further effectiveness to benefit the general or specific population with semantic applications (Fig. 2).

3.2.3 Activity Tracking

Smartwatches embedded with sensors and algorithms help track the different activities related to daily wellbeing. These range from sleep, physiological parameters, physical activities related to wellbeing and fitness, food logs or calorie intake procedures, water intake or hydration information. So, overall, multiple activities are derived and divided into zones to promote fitness and wellbeing. However, a large amount of data generated through these devices gives rise to pervasive applications development. Multiple data features and insights can be created through an enormous amount of data generated for different activities. These features can result in ambient and IoT-related applications that can effectively monitor a patient or individual physiological performance that can act as crucial information relating to the state and condition of the patient during pandemics (for instance, if the person has been infected and is undergoing isolation, or is healthy without any infection, or has presented a positive result). Therefore, these applications or solutions can be beneficial and decisive in controlling and managing pandemics (Fig. 3).

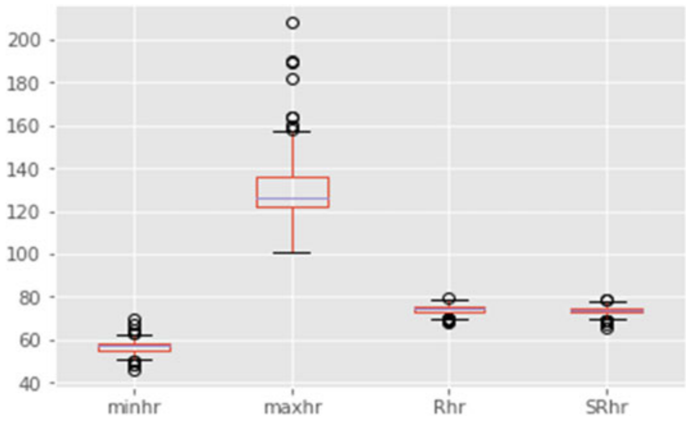

Fig. 3 This represents a box plot distribution of data for different features extracted for the implementation of healthcare solutions. It represents different activities and their parameters during different time zones during the day. Activities parameter values relate to physiological signals for minimum, maximum, resting and sleeping heart rate values extracted through a wearable smartwatch

3.2.4 Context-aware Location Service

Furthermore, a smartwatch-oriented solution or platform can also act as a GPS tracking device, along with subsidiary devices or networks to guide emergency services and stakeholders to a person's location. In the case of an emergency event it can indicate the onset of abnormal disparities. Specifically, this method can be very beneficial for people living in rural and urban areas who require observation under self-health management or rehabilitation for any postoperative cardiac surgery and other cardiac conditions.

For example, if someone in rehabilitation or under clinical supervision is alone or without support and an emergency event occurs, this solution can act to initiate procedures to contact associated stakeholders, family, or friends. This decreases the emergency response time for paramedical services or related staff. It will also be effective in the event of pandemics breakouts to monitor and observe the location-based activity of patients or populations to address and control situations well in advance (Fig. 4).

3.3 Technological Advances in Healthcare

This section highlights the use of technological advances or technology-based solutions to help disadvantaged people, support assisted living, cater to specific vulnerable groups such as people suffering from impairments, people living in isolation, and people with obvious user requirements, in order to deal with certain health conditions. A wide range of solutions and applications is applied to support individual

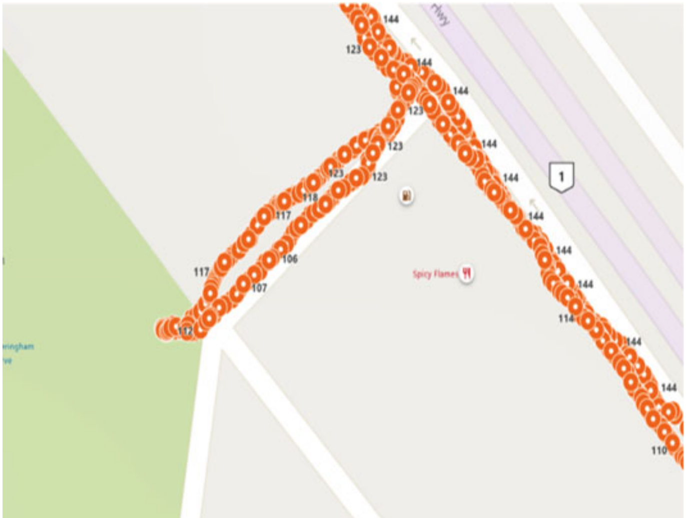

Fig. 4 This presents a context-aware location service or GPS tracking through Fitbit activity or GPS location dashboard. A real-time activity tracking service is also available for tracking purposes. This can be implemented or installed on the design side of health systems to monitor patient movements or activities. Also, GPS coordinates or activity tracking validate GPS accuracy during an endured activity. Therefore, Fitbit GPS accuracy can be an advanced feature for the accurate location of an individual or patient during emergency responses or procedures

health and support health professionals, care workers and other support staff to meet the needs of all involved stakeholders on a daily basis. We cover some examples in the general adoption section about technologies that are prevalent and adopted for the self-catering and healthcare areas.

3.3.1 Generalised Solutions

Healthcare professionals and patients use emergency pendants or control procedures for information about emergency conditions or situations [30], e187. Traditional emergency response systems include first generation emergency response systems that utilise a unit and switch or pull code system. However, second and third generation systems involve the use of a pendant or necklace that liaises with an emergency button to communicate with a responder, whereas the latest systems incorporate automatic detection and response, enabling remote care. Patient emergency response systems provide user safety and independent living; however, possible improvements can be made in the design of the system and integrating the service with the technological part of complex caring practices rather than plug and play devices. Studies are extensively examining different features such as usability, responsiveness and the effectiveness of the technology, including the development of long-range pendants, waterproofing, the inclusion of a global positioning system, alarms, automatic connection to health personnel and an automated dispatch sound. According to this study outcome, the development of ambient wearable IoT solutions can lead to next-generation automated devices. It can also effectively cater to basic or generalised needs in addition to a pandemic response.

3.3.2 Pandemic-Oriented Solutions

(1) Mobile solutions and applications: Islam et al. [19], 145,601–145,610 present mobile applications developed for COVID-19. They involve a systematic review of existing mobile applications across major mobile application stores. They include application features and functionalities presenting factors for future application design through information system design characteristics [6], 1–1. The study highlights smartphone applications designed to contain the spread of the COVID-19 virus. Applications covered include user permissions required for tracking and tracing. Data use is transferred to the analytic centre from the user device and security measures are deployed through these applications for user privacy and security.

(2) Contactless transactions: Wearables or smartwatches comprising NFC technology enable cashless payments or transactions, effectively preventing the spread of the COVID virus during pandemics. Pal et al. [23], 427 submit that during the pandemic, concerns were raised by the public about virus transmission through the handling of currency notes and coins. The public were curious to know the medium of the spread of infection via the physical currencies being circulated. The study finds that human-to-human transmission is possible through cash and coins because the COVID virus seems stable on smooth surfaces. Thus infection can even be detected 2–4 days after coming into contact with the virus. However, the smartwatch feature of cashless transactions can be an advantage in restricting the spread of infection as it involves no touching of high contact surfaces or equipment, including physical currency.

(3) Contact tracing: Ahmed et al. [2], 134,577–134,601 present smartphone abilities and tracking traits through embedded features such as GPS, Wi-Fi and inbuilt Bluetooth capabilities to communicate to nearby devices or other smartphones. These features make them ideal devices for automated and efficient contact tracing. Ahmed et al. [2], 134,577–134,601 present centralised, decentralised and hybrid architectures for application design and use for contact tracing. However, similar features in wearable smartwatches promote them as crucial components or integrated devices in the above architecture schemes. These inbuilt pervasive and ubiquitous features can enhance the adoption and deployment of wearable IoT solutions for generalised and healthcare needs, addressing requirements for involved stakeholders and effective contact tracing.

3.4 *Limitation*

One of the main challenges that require attention relates to the privacy and security issues of the devices involved in the network. A large amount of data is generated through wearable devices, and that data is continuously shared among the devices and further. Secondly, for data generated for physiological parameters or that is health-related and involves medical and allied health professionals, there is the requirement for the optimum privacy of the patient or individual. Therefore, authentication procedures for authorised access, data privacy, sematic data analysis and related procedures should be efficiently deployed.

3.4.1 Security

Additionally, such solutions should minimise any security flaws and threats within the local area network and extended network of distributed devices optimised within the platform. Moreover, data or information that can be attached to social networks, individual user interfaces or healthcare applications should be dealt with at a high level of security in order to avoid passive and other security attacks. Azad et al. [6], 1–1 present a study related to mobile applications used during the COVID-19 pandemic. Data use and transfer to an analytic centre from the user devices should maximise security measures deployed through these applications for user privacy and security.

Bodin et al. [11], 1–5 discuss integrating smartwatch device-related IoT or solutions that can be embedded for enterprise information technology, perhaps covering the dimensions to integrate smartwatch devices with backend systems and establishing a relationship or the correlation of the data analytics side of the system with a foolproof security dimension for the entire system. It further details a pervasive and analytics system to preserve and protect the security needs of the user, thus further establishing the design and development of secure and intelligent smartwatch applications.

Major flaws or concerns can be the attacks on wearable IoT systems that raise security and privacy concerns, specifically through integrated pervasive devices such as smartwatches, smartphones, or tablets. Siboni et al. [29], 741–750 illustrate that attacks increase the concern levels in the enterprise environments by opening entry points for malicious activities and weakening the digital perimeter within the network. Similarly, [16], 391–403 demonstrate that the increasing use of wearables or smartwatch devices among IoT and cloud solutions for healthcare can threaten to exploit and exfiltrate user data. This study presents different types of user data carried on a smartwatch, including contact information, messages, and physiological data, and highlights the methods or techniques which can be adopted to exfiltrate these devices by an adversary. Some other examples of security attacks on wearable devices involve [12], 19–30 presenting a detailed overview of security and privacy exposures on wearable devices, including authentication, low processing, or computing power for security mechanisms indicating this technology lacks security, and weaknesses prevail for outsider security threats and attacks. Security side studies are covered to illustrate the limitations of foolproof IoT solutions or considerations to be seriously undertaken while deploying healthcare applications, solutions, and systems.

3.4.2 Privacy

Privacy involves physiological user data, healthcare user and stakeholder procedures. The applicability of solutions involves platforms and applications related to various healthcare stakeholders that should ensure high confidentiality for all users, ensuring proper authentication and encryption procedures. Some further specific privacy concerns involve [3], 153–179 presenting a review of remote patient care and monitoring applications; results drawn include privacy threats involving unauthorised access to user data, breaches involving data threats and impersonation attacks. Puppala et al. [25], 5–8 propose a model to protect patient privacy through different technologies and practices, including restrictive access to data and technical de-identification. Results present unauthorised access to data and data security thefts as negligible. User or data privacy is a crucial asset in modern pervasive and IoT applications. Large amounts of data are streamed between different devices and platforms, accommodating an enormous number of different healthcare stakeholders during different times of the day. User data can involve sensitive physiological information, communication, or emergency response information. Thus data is shared at different layers or designs of the systems. Smart applications or systems generate enormous amounts of data through embedded or deployed sensor nodes, which are communicated further to other devices and servers. Data analytics play a significant role in modern smart or IoT solutions, generating insights for distributed population numbers to draw effective results and insights from this. Data security and privacy will play a pivotal role. The semantic side of these intelligent applications or solutions involves data intelligence features that should be well-protected and preserved.

4 Discussion and Conclusion

Smartwatch monitoring in most studies focuses on activity recognition, and this criterion is well-researched and presented. However, the efficient and pervasive features of smartwatches, like embedded sensing, communication, and data transfer capabilities, can serve as a practical IoT component to monitor vital health parameters. Machine learning methods can effectively diagnose the onset of severe cardiac disorders such as heart attacks and strokes during pandemics and in general or adverse wellbeing scenarios. Moreover, the commercial availability and user acceptance of smartwatches can serve better and extended purposes towards patient and general monitoring comparatively or in addition to distributed sensor networks or wearable body area networks that are effectively presented in off-the-shelf smartwatch technology [18], 39–44.

Furthermore, as mentioned under the COVID-19 section and cardiac subsection in this chapter, the evidence in the studies demonstrates that pandemics such as COVID-19 have contributed to cardiac-related fatalities or post-COVID disorders after contraction of the infection. However, people above a particular age group or those suffering from any underlying cardiovascular conditions can also be well-monitored in advance, thus reducing the mortality rate during pandemics. Wadhera et al. [31], 159–169 has presented hypertensive disease-related fatalities during the onset of the pandemic in the United States. Banerjee et al. [8] investigated cardiovascular diseases related to increased mortality risks through COVID, along with the impact or reduced supply and demand for cardiovascular-related disease services that can reduce the mortality rate during and after the pandemic. Thus the use and implementation of IoT-related solutions can certainly contribute to establishing the cause or onset of infections, promote their management during the spread and determine the outcome of infections towards their final eradication through contact tracing techniques.

5 Future Works

Pervasive or intelligent devices such as smartwatches with their computing characteristics have the potential to contribute to preventing the transmission of and management of infections or disease-related symptoms well in advance. They can unleash prospective dynamics in developing IoT networks and artificial intelligence guided machine learning solutions to detect disparities, enable contact tracing mechanisms, promote management for context-aware locations, and identify vulnerable groups of people impacted by the disease, specifically during pandemics. Thus they can help to promote emergency response procedures in advance, guiding healthcare staff, including paramedical staff or ambulance drivers, to the specified or recorded location history and attend to patients and the public in most need during pandemics. The massive contribution of big data via these devices can also lead to the development of data analytic solutions and insights for multiple involved data features for physiological activity, exercise patterns, food logs and health parameter monitoring. However, other primary concerns for IoT frameworks or solutions involve monitoring and addressing security and privacy challenges for robust system development and outcomes. These solutions will benefit the healthcare industry but will also be applicable in other industries apart from the healthcare sector.

References

1. Aced López, S., corno, F., De Russis, L.: Supporting caregivers in assisted living facilities for persons with disabilities: a user study. Univer. Access Inf. Soc. **14,** 133–144 (2015).https://doi.org/10.1007/s10209-014-0400-1
2. Ahmed, N., Michelin, R.A., Xue, W., Ruj, S., Malaney, R., Kanhere, S.S., Seneviratne, A., Hu, W., Janicke, H., Jha, S.K.: A survey of COVID-19 contact tracing apps. IEEE Access **8**, 134577–134601 (2020)
3. Amaraweera, S.P., Halgamuge, M.N.: Internet of Things in the healthcare sector: overview of security and privacy issues. In: MahmooD, Z. (ed.) Security, Privacy and Trust in the IoT Environment. Cham: Springer International Publishing (2019)
4. Arampatzis, T., Lygeros, J., Manesis, S.: A survey of applications of wireless sensors and wireless sensor networks. In: Proceedings of the 2005 IEEE International Symposium on Mediterrean Conference on Control and Automation Intelligent Control. IEEE, pp. 719–724 (2005)
5. Atzori, L., Iera, A., Morabito, G.: The Internet of Things: a survey. Comput. Netw. **54,** 2787–2805 (2010). https://www.sciencedirect.com/science/article/pii/S1389128610001568
6. Azad, M.A., Arshad, J., Akmal, S.M.A., Riaz, F., Abdullah, S., Imran, M., Ahmad, F.: A first look at privacy analysis of COVID-19 contact tracing mobile applications. IEEE Internet of Things J. 1–1 (2020)
7. Badica, C., Brezovan, M., Badica, A. An overview of smart home environments: architectures, technologies and applications. BCI (Local) 78 (2013)
8. Banerjee, A., Chen, S., Pasea, L., Lai, A. G., Katsoulis, M., Denaxas, S., Nafilyan, V., Williams, B., Wong, W.K., Bakhai, A.: Excess deaths in people with cardiovascular diseases during the COVID-19 pandemic. Eur. J. Prevent. Cardiol. (2020)
9. Bansal, M.: Cardiovascular disease and COVID-19. Diabetes Metabol. Syndr. Clin. Res. Rev. **14,** 247–250 (2020). https://www.sciencedirect.com/science/article/pii/S1871402120300539
10. Bhatla, A., Mayer, M.M., Adusumalli, S., Hyman, M.C., Oh, E., Tierney, A., Moss, J., Chahal, A.A., Anesi, G., Denduluri, S., Domenico, C.M., Arkles, J., Abella, B.S., Bullinga, J.R., Callans, D.J., Dixit, S., Epstein, A.E., Frankel, D.S., Garcia, F.C., Kumareswaram, R., Nazarian, S., Riley, M.P., Santangeli, P., Schaller, R.D., Supple, G.E., Lin, D., Marchlinski, F., Deo, R.: COVID-19 and cardiac arrhythmias. Heart Rhythm **17**, 1439–1444 (2020). https://www.sciencedirect.com/science/article/pii/S1547527120305944
11. Bodin, W.K., Jaramillo, D., Marimekala, S.K., Ganis, M.: Security challenges and data implications by using smartwatch devices in the enterprise. In: 2015 12th International Conference & Expo on Emerging Technologies for a Smarter World (CEWIT), 19–20 Oct. 2015, pp. 1–5 (2015)
12. Ching, K.W., Singh, M.M.: Wearable technology devices security and privacy vulnerability analysis. Int. J. Netw. Secur. Appl. **8**, 19–30 (2016)
13. Commission, P.: Economic implications of an ageing Australia. Productivity Commission, Government of Australia Research Reports (2005)
14. Corno, F., De Russis, L., Roffarello, A.M.: A Healthcare Support System for Assisted Living Facilities: an IoT Solution. In: Proceedings 2016 IEEE 40th Annual Computer Software and Applications Conference Workshops, vol. 1**,** 3pp. 44–352 (2016) <Go to ISI>://WOS:000389533300045
15. Do, H.M., Pham, M., Sheng, W., Yang, D., Liu, M.: RiSH: a robot-integrated smart home for elderly care. Robot. Auton. Syst. **101,** 74–92 (2018). http://www.sciencedirect.com/science/article/pii/S0921889017300477
16. Do, Q., Martini, B., Choo, K.-K.R.: Is the data on your wearable device secure? An Android Wear Smartwatch Case Study. Softw. Pract. Exp. **47**, 391–403 (2017). https://onlinelibrary.wiley.com/doi/abs/https://doi.org/10.1002/spe.2414
17. Dohr, A., Modre-Opsrian, R., Drobics, M., Hayn, D., Schreier, G. The internet of things for ambient assisted living. In: 2010 Seventh International Conference on Information Technology: New Generations. IEEE, pp. 804–809 (2010)

18. Filippoupolitis, A., Takand, B., Loukas, G.: Activity recognition in a home setting using off the shelf smart watch technology. In: 2016 15th International Conference on Ubiquitous Computing and Communications and 2016 International Symposium on Cyberspace and Security (IUCC-CSS), 14–16 Dec, pp. 39–44 (2016)
19. Islam, M.N., Islam, I., Munim, K.M., Islam, A.N.: A review on the mobile applications developed for COVID-19: an exploratory analysis. IEEE Access **8**, 145601–145610 (2020)
20. Islam, S.R., Kwak, D., Kabir, M.H., Hossain, M., Kwak, K.-S.: The internet of things for health care: a comprehensive survey. IEEE Access **3**, 678–708 (2015)
21. Ko, J., Lu, C., Srivastava, M.B., Stankovic, J.A., Terzis, A., Welsh, M.: Wireless sensor networks for healthcare. Proc. IEEE **98**, 1947–1960 (2010)
22. Nomura, M., Mclean, S., Miyamori, D., Kakiuchi, Y., Ikegaya, H.: Isolation and unnatural death of elderly people in the aging Japanese society. Sci. Justice **56,** 80–83 (2016). http://www.sciencedirect.com/science/article/pii/S1355030615001574
23. Pal, R., Bhadada, S.K.: Cash, currency and COVID-19. Postgrad. Med. J. **96,** 427 (2020). http://pmj.bmj.com/content/96/1137/427.abstract
24. Perret-Guillaume, C., Joly, L., Benetos, A.: Heart rate as a risk factor for cardiovascular disease. Progr. Cardiovasc. Dis. **52,** 6–10 (2009). http://www.sciencedirect.com/science/article/pii/S0033062009000322
25. Puppala, M., He, T., Yu, X., Chen, S., Ogunti, R., Wong, S.T.C.: Data security and privacy management in healthcare applications and clinical data warehouse environment. In: 2016 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), 24–27 Feb, pp. 5–8 (2016)
26. Rashidi, P., Mihailidis, A.: A survey on ambient-assisted living tools for older adults. IEEE J. Biomed. Health Inf. **17**, 579–590 (2013)
27. Rich, M.W.: Heart failure in the 21st century: a cardiogeriatric syndrome. J. Gerontol. Series A **56,** M88–M96 (2001). https://doi.org/10.1093/gerona/56.2.M88
28. Saito, H., Kagiyama, N., Nagano, N., Matsumoto, K., Yoshioka, K., Endo, Y., Hayashida, A., Matsue, Y.: Social isolation is associated with 90-day rehospitalization due to heart failure. Eur. J. Cardiovasc. Nurs. **18**, 16–20 (2018). https://doi.org/10.1177/1474515118800113
29. Siboni, S., Shabtai, A., Elovici, Y.: Leaking data from enterprise networks using a compromised smartwatch device. In: Proceedings of the 33rd Annual ACM Symposium on Applied Computing. Pau, France: Association for Computing Machinery (2018)
30. Stokke, R.: The personal emergency response system as a technology innovation in primary health care services: an integrative review. J. Med. Internet Res. **18,** e187 (2016)
31. Wadhera, R.K., Shen, C., Gondi, S., Chen, S., Kazi, D.S., Yeh, R.W.: Cardiovascular deaths during the COVID-19 pandemic in the United States. J. Am. Coll. Cardiol. **77**, 159–169 (2021)
32. Warnier, M.J., Rutten, F.H., Kors, J.A., Lammers, J.W.J., de Boer, A., Hoes, A.W., de Bruin, M.L.: Cardiac arrhythmias in adult patients with asthma. J. Asthma **49**, 942–946 (2012). https://doi.org/10.3109/02770903.2012.724132
33. Wood, A., Virone, G., Doan, T., Cao, Q., Selavo, L., Wu, Y., Fang, L., He, Z., Lin, S., Stankovic, J.: ALARM-NET: wireless sensor networks for assisted-living and residential monitoring. University of Virginia Computer Science Department Technical Report **2**, 17 (2006)

Making the Invisible Visible: A Science and Society View of Developing Non-invasive Thermal Technology

N. Amini, M. Mann, C. Hempton, T. King, and J. Loy

Abstract Technological innovations that are detached from social context are problematic, particularly for those who are already structurally disadvantaged by factors such as race, disability, geography, job security and health. Design that happens in context provides opportunities for innovative thinking and creative solutions that anticipate the complexities of real-world implementation and improve the potential for technology adoption. This chapter describes an interdisciplinary project that involved the development and critique of a "provotype" health intervention from the perspective that technology is never benign and that artifacts have politics. Working across disciplines on complex, real world issues can be difficult in university systems frequently designed to foster and reward disciplinary specialisation. This work highlights the necessity to include interdisciplinary working practices, and build an integrated body of knowledge, particularly in circumstances that require rapid responses to global problems, such as COVID-19.

Keywords Non-invasive technology · Provotype health intervention · COVID-19 Monitoring · Body temperature detection · Ethics of health intervention · Social equity · Privacy in surveillance · Technological solutionism

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1 Introduction

Technology is never benign and artifacts have politics [56]. In the context of turbo-charged developments, designed to combat a global pandemic, existing inequalities are likely to be highlighted or exacerbated. The events of the year 2020 changed perceptions about the vulnerability of people around the world. In *The Great Leveler*, economic historian, Walter Scheidel [45], argues that widespread plagues are one of only four circumstances that may bring about a more equitable sharing of wealth and vulnerability in society (along with revolution, war and state collapse) [45]. Whilst the 2019 novel coronavirus has killed millions of people across the globe relatively indiscriminately, in an interview with The Guardian at the end of April 2020 Scheidel warned that it was yet to be seen whether social inequality would be impacted. Those employed in low-wage or insecure work, and particularly front-line workers, have been compelled to put their bodies (and lives) on the line to put food on the table and low-income communities have been ill-equipped to provide life-saving supplies, such as masks and oxygen. Speculating about the swift discovery of a vaccine, Scheildel predicted that "science will save the status quo" [12]. While the development of vaccines has been a huge relief for many, timely access to them has been anything but equitable (even in nations of the Global North (a group of countries defined by socio-economic and political characteristics, such as the UK, the US and Australia), with those wishing to access a vaccine from poorer countries pushed to the back of the line [57]. Scheidel notes that while examples of social inequality are not new, the difference in how COVID-19 has impacted various segments of society means that "we're becoming very painfully aware of them". There is a risk that new technologies will reinforce, cement and exacerbate existing social inequalities.

In response to the COVID-19 pandemic, various preventive public health measures have been adopted at a population-level, and in some places are enforced by the Government. A range of non-technological interventions have been utilised, including mask-wearing and physical distancing, travel-restrictions, curfews, and lockdowns. Other adopted interventions utilised various forms of technology, such as contact tracing apps and the use of QR codes for venue-check-ins, in addition to the potential of 'vaccination passports'. Additionally, temperature screening has been widely adopted, with those wanting to move through both public and private spaces—e.g., airports, retail stores—subject to temperature screening both to filter potential COVID-19 positive cases (indicated by a high temperature). These are in part preventative but also to visibly reassure staff and the public that biosecurity concerns are being addressed. Around the world, however, there have been small but vocal protests against the necessity of both non-technological and technological interventions [24, 35, 49]. While some who resist such technologies and mandated practices have been labelled as 'Covidiots' [50], exploring the underlying drivers of this resistance is crucial to the implementation of new technologies designed to keep the world safe from further pandemics, and their overall efficacy. Rather than being a result of only poor or misinformation, conspiracy theories or ignorance, the resistance to COVID-19 technologies requires careful unpacking.

One of the underlying concerns about COVID-19 related technologies relates to the potential for breaches of privacy and expanded state surveillance. Gathering and sharing personal information via apps, designed to capture the movement of potentially infectious individuals, has been resisted by some people on the basis of privacy. For example, in Australia the COVIDSafe app developed by the Australian Federal Government has received such a low uptake by the population that it has been rendered useless [52]. Another concern highlighted the unequal ways in which 'safety' measures, such as lockdowns, impact particular segments of the population, particularly those who work in hospitality, retail and the entertainment industry. This is in contrast to those who can conduct their employment from the relative safety of their homes. The context of COVID-19, in which social inequalities are magnified, provides an opportunity for reflection on the ethical and social implications of rapidly developing and deploying technology across heterogenous populations. Thus, there is a need for technology which can be customised for individuals and communities to improve its integration into society in order for it to more effectively alleviate emerging challenges. However, even bespoke technological solutions would bring their own ethical and social implications, which must be considered.

In this chapter we describe an interdisciplinary project that involves the creation of a provotype—in the form of a personal wearable temperature device—and the ethical considerations raised by the very possibility of that technology. A provotype, or provocative prototype is designed as an MVI, or minimum viable concept, to provoke a reaction and discussion—in this case in order to help investigate the potential impact of an emerging technology on individuals and community groups. In this chapter, we provide an introduction to the project concept, and describe the aims of the project and the team, as well as situate the research in relevant, cross-disciplinary discourse. We explain the reasoning behind the development of the provotype and the debate it is intended to prompt. We then consider some of the issues that were raised by the integrated team of engineering, design and social science in response to the proposal. A key objective was to question a technology being presented as a "solution" for a social problem. This relates to the work of Morozov and Carr [6, 38] on technological solutionism and his critique of technology as solution. This also relates to concerns that technologies influence, shape, and cement extant structural/systemic issues, and there is a need to be attentive to the broader socio-political contexts in which technologies are introduced as solutions to social problems. This integration of practice was seen as key for adoption and compliance by both the design engineers and the social scientists, and yet that collaboration is still a rarity in technology-based projects.

Finally, we reflect on the experience of interdisciplinary work, particularly as it is integrated into engineering training and practice and including the challenges of conducting interdisciplinary research for healthcare solutions. This approach highlights the deep reflective work that should occur in order to progress an interdisciplinary healthcare project, such as this, to the point of traditional data-collection (from recruited participants). Whilst the response to events such as global pandemics frequently demands the rapid creation of technical solutions, in this ‘thought experiment’ we deliberately take a more self-conscious route that allows time for the untangling of interdisciplinary knots, assumptions and, most importantly, unanticipated consequences.

2 Technology and Society in the Covid-19 Context

Introducing any product into public use, whether based on a new technology or not, comes with responsibilities. Product safety testing is an essential requirement for commercial products and is controlled by standards, for example from the Office of Product Safety and Standards in the UK. For medical products the regulations are rigorous. Although the products that are the subject of this study could be classed as medical products as they are involved in the “diagnosis, prevention, monitoring, treatment or alleviation of disease” (WHO 2003), the concept is intended to be indicative and informative, rather than definitively the basis for a commercial product, For medical devices and healthcare products, there are numerous organisations around the world that regulate the approval process to ensure that products are properly tested and deemed within an acceptable level of risk to use. The global overview and guiding principles of these regulations are outlined by the World Health Organisation [55], and countries have their own approval bodies, such as the Food and Drug Administration (FDA) for the US, and in Australia, where the pilot study for this chapter was conducted, the Therapeutic Goods Administration (TGA). However, these approvals are predominantly focussed on the medical over the social impact of the use of the products. The World Health Organization definition of problems that should be monitored after the introduction of a medical device does include “an undesirable outcome associated with the use of the device” that “may not lead to an adverse effect but corrective or preventative measures are required”. However, the focus is on performance standards, rather than social engineering.

The potential broader impacts of medical devices and healthcare products on behaviour and attitudes are frequently overlooked when there is a commercial imperative [9]. However, when products are intended to be of positive benefit in a healthcare response, and especially in a heightened alert situation such as a pandemic, it is pertinent to consider a more holistic view of the impact of that product on shaping society and to plan for the future they may engender. Essentially, the negative as well as positive implications of the introduction of the technology need to be considered for all stakeholders and not only for those protecting business operations, or even shielding vulnerable members of society. This is a complex issue, for example the use of a technology could impact groups in society disproportionately if a dominant group has control of its use, and discrimination over when, where and how it is used. In addition, in the case being discussed where the detection and communication of an infectious disease is involved, guidelines on how to respond to a positive result from one of these products would be a necessity for whoever was administering the test. Beyond this, the reactions of groups of people in the vicinity of the test subject, or potentially affected by a positive result, need to be anticipated, and guidelines to address these circumstances established.

Finally, the impact on the person being tested in terms of being put in the position of needing to be tested, questions around consent, particularly in a public environment, and the stress of a positive result, particularly in a public setting, need to be properly considered. The negatives, and not merely in terms of the physical and emotional wellbeing of those involved but also with respect to the broader effects on society and societal norms as a whole, need to be researched and understood. Lateral and active transition research needs to occur, instead of, or at a minimum as well as longitudinal, reflective study, due to the significance and urgency involved in the introduction of new technologies during a pandemic. The need to build a new normal that does not disproportionately have an adverse effect on sections of society or individuals should be integral to the planning and preparation. The risks to groups vulnerable to social engineering need to be evaluated and mitigated against and methods within a transition research methodology identified and tested. These challenges require teams that combine engineering and the social sciences. More than that, they necessitate a self-awareness of the need to appropriately frame the issues as the basis for actively integrating practice to develop socially responsible technology in response to this pandemic.

2.1 Non-Invasive Monitoring and Communication Tools: Pilot Study

The premise of the research study described in this chapter is that from the inception of any project, through the development of ideas and strategies, to their integration into society, an interdisciplinary approach is essential to ensure that ethical, environmental, social and economic factors are thoroughly, and holistically considered. From which perspective the idea is generated will impact the framing of the problem and the brief, and ultimately impact the success of the idea both in the immediate and long-term contexts.

This pilot study grew from COVID-19 technology discussions within an engineering design context on the ethical implications of designing the provotype for this particular purpose and the challenges for a disciplinary team to adequately anticipate the implications of its development. While confident that a personal device for the detection and communication of the body temperature pf individuals and those around them could be easily built and a product launched, the question was, should it be? It is important to note that this conceptual stage of the project happened before the interdisciplinary group was constructed. The subsequent research team was assembled from personal and professional networks within the university and coalesced around a seeding grant from the Deakin University Science and Society Network [39], which 'supports science-literate social research and socially-engaged science that makes an impact'.

The team now consists of an engineer, a designer, a global citizen researcher, an anthropologist and a bioethicist. This team was curated to provide contrasting views on priorities and practice in the development of technological health-care responses to inherently social problems. Because this is an ongoing project of collaboration, we use the present tense to describe our progress. The trajectory of the research involves the completion of focus groups to ponder over the provotype and spark discussions on its implications if integrated into society. The aim was to use this project as the basis for developing insight for other engineering teams on heightening awareness in their teams on the criticality of an interdisciplinary approach for healthcare design projects.

3 COVID-19 Monitoring and Communication in a Public Setting

There are a number of preventative measures actively being used across the globe as a basis to respond to and prevent the spread of COVID-19 in this pandemic. There are potential positive and negative effects the use of non-invasive technology has on the physical and emotional wellbeing of (a) the user (b) others. Non-technological preventative measures include, for example, improved hand washing techniques, social distancing of 1.5 m or more and using face masks in crowded areas [36]. A definitive vaccine which provides immunity to the virus would ideally be the answer, however, the development of such a cure is hindered by time, money, resources and COVID variants. In some instances where the virus took over the sectors of a society, government authorities resorted to extreme measures by enforcing community lockdowns [8]. With the increase in population densities across major cities around the world over the last century, and the need for continuous human movement and interaction in current workplace organisation, community lockdowns can have a damaging long term as well as short term economic effect. However, relying solely on non-technological measures to minimize of the number pf people contracting the virus whilst avoiding lockdown, death rates inevitably increase [16]. Without a definitive vaccine, effective against potential variants, a balance of appropriate measures are required which could be a combination of medication, technological and non-technological solutions, in order to avoid complete community lockdowns. Therefore, the public health response is crucial in enabling societies to function as ‘pandemic-normal’ while minimizing the number of infections and related deaths [27]. The various types of symptoms shown by individuals can vary from asymptotic, mild symptoms, pneumonia to death [46]. More commonly, mild symptoms consist of fever, cough, loss of smell or taste [46]. A mild symptom which has received much regard for accurate detection is fever, where low grade fever has been classified as 37.8–38.8 °C [25]. This project involves investigating the practicality (technical and social) and impact of detecting and reporting elevated temperatures in individuals or several individuals in group settings.

A number of studies have investigated the use of various forms of non-invasive technology to identify and monitor the users' vital signs. The subtle changes in basic vital signs, which may not be apparent to the individual, can offer earlier signs of virus-infection compared to those associated with self-reported symptoms [29]. For mass detection, infra-red imaging cameras are an example of non-invasive technology which can be utilized at airports, and has been in previous pandemics (i.e. H1N1 influenza) [21]. The utilization of thermal imaging cameras was re-introduced for the COVID-19 pandemic, and its application extended to other virus transmission hot spots, such as shopping centres. In literature, Khan et al. reported the use of the infra-red thermal imaging camera in detecting temperature in children and compared the accuracy for detection in adults [30]. It was reported, however, that this technology may not be the safest to use for fever detection in adults during a pandemic because the accuracy of this tool may diminish in less controlled conditions. In another study, Adams et al. screened a number of infra-red thermal imaging cameras in order to determine whether the accuracy of the different models falls within the range of 0.3 $\pm$ 0.1 [1]. It was found that this method poses a potential risk for frontline fever detection as it lacks measurement repeatability which can impact sensitivity of the data.

Combining wearable technology with the Internet of Things (IoT) has been reported by Khan et al. and puts forward the possibility of doctors remotely monitoring patients health and vital signs [28]. Sugathan et al. looked at integrating biosensors in shirts to identify the wearers heart rate, electro dermal activity and skin temperature [47]. Escobedo et al. reported a smart bandage with integrated batteryless NFC tag that can monitor the status of wounds or respiratory diseases such as asthma or COVID-19 [15].

With these taken into consideration, the provotype in this chapter proposes a re-engineering [15] of the non-invasive device specifically for the application of integration into society to make visible the invisible symptoms of COVID-19. However, as reiterated throughout this chapter, such an integration would come with risks and it is the impact of those risks that this project highlights need to be carefully considered and understood before implementation. In the next section we describe the development of the provotype itself, before continuing to identify such risks.

The basis for the research provotype was 'making the invisible visible'. The drivers for this approach would be applied differently for different situational contexts. In this pilot study, the provocation was intended to prompt discussion from different disciplinary perspectives. The concepts modelled certainly should not be considered as resolved design or product outcome, but rather a practical illustration for the focus group and interdisciplinary team, of different applications that could, very realistically be developed into a commercial outcome. The research team anticipate that versions of these types of products could well become available across the world in the near future, depending on the spread of the virus and the control brought about by vaccine development. This is because the approach aligns to the current discourse in the product design discipline on COVID-19 application development.

The majority of COVID-19 products featured in 2020 and the start of 2021 in industry and research publications have focussed on providing personal protection to minimise the risk of virus transmission. These interventions can be classified into three groups according to the dynamic between the product and the individual user or users. (a) They may be passive products, designed to respond to changing needs in a 'COVID-safe' landscape, for example the Pentatonic Studio bring-your-own cutlery set [4], or the Christophe Gernigon large, clear plastic hoods hung over restaurant tables to isolate diners at the same table [5]. (b) Alternatively, they may be active products, such as the Guardian G-Volt masks [3]. According to product manufacturer LIGC, which manufacturers filters for air purifiers and air conditioning, these masks are produced to a higher filtration standard than N95 respirator masks, that are the clinical standard in COVID-19 protective masks. Incidentally, these were launched in March 2020, at a time when the WHO was advising only those in direct contact with a diagnosed patient wear a mask. (c) They may also be responsive products, that is they provide a response or feedback to the user. In this case, the user may be someone other than the person being tested, which creates a potential conflict. One example is the Buckle Mask, by Above design studio. This mask has a built-in filter that changes colour as absorbs particles, showing the user—and those in proximity—how effectively the mask is likely to be functioning at a particular point in time. This third group of products is the focus for the pilot project in this study.

3.1 Provotype Proposal

Two provotypes were developed to prompt discussion on the research topics. For one, the intent was that the product would be used to detect body temperature in others and inform the user. In the other, the temperature detection would be applied to the wearer, with results communicated to others in the vicinity.

The first provotype provided an overt provocation. A brightly coloured, extended bracelet design, with LEDs around the wrist, fed from a sensor and battery attached to the underside of the wrist, as shown in Fig. 1a. The device operates such that the circuit board physically connects to the thermocouple and display and reader. The circuit board dictates at what temperature the thermocouple must reach before the display and LED lights activate. In the case of this provotype, LED lights will turn red when the thermocouple exceeds a surface body temperature of 37.8 °C. This would then alert both the user and those in the vicinity of a change in temperature status for the user.

The second provotype was designed to be less overt than conventional temperature readers, which usually involved holding a temperature 'gun' within a metre of a person's forehead. This one was designed using a thermocouple that allowed the user to stand up to 1.5 m away, and, if desired, direct the device from a more subtle position for example from the level of the hip, as shown in Fig. 1b. Equally it could be used in a more focussed stance, pointed at the subject. The thermocouple was a 4 cm long, metal cylinder, diameter 1.5 cm fed by a cable attached to a circuit board, that could remain in the pocket of the user. In the instance a surface body temperature exceeding 37.8 °C is detected, the circuit board would alert the application on the

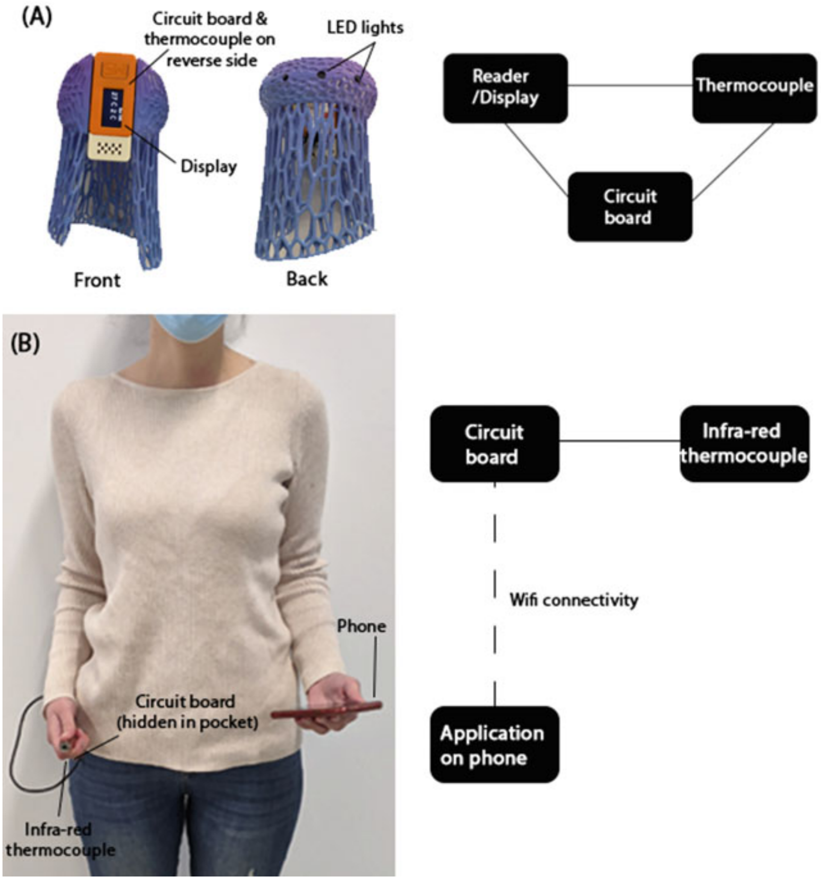

Fig. 1 Images and mode of operation for **a** the customisable 3D printed bracelet provotype and **b** the detached Infra-red temperature sensing provotype

phone via wi-fi connectivity and the phone would vibrate, alerting the user, but not the subject or those in the vicinity.

These provotypes were designed to be operable, rather than purely conceptual, to aid the demonstration in a focus group setting of the ideas. Both included appropriate electronics. Part of the idea behind the bracelet-type model was that the wearer could define the level of visibility of the product. This could be determined by the situation (whether the individual wanted to draw attention to the negative indication on the bracelet to those around them) or by the personal, aesthetic preferences of the individual. This choice of form is now possible because of developments in additive manufacturing technology (also known as 3D printing), which allows a level of accessible, bespoke fabrication not possible with conventional manufacturing technologies. The bracelet provocation was fabricated using powder-based, multi jet fusion (MJF) technology as this produces an end-use product, that is the parts printed are robust and therefore suitable for use in the focus group, and also has the facility to add colour during the print itself. This enables viable customisation.

The ability to demonstrate the viability of the provocation as the basis for a commercial product was deemed key for the project in order to create a more genuine response to the realistic potential for its use. It also helped to ground the proposition for the team, ensuring an interdisciplinary language imperative.

4 Ethical and Social Implications

The ethical and social implications of various health measures and surveillance activities may differ depending on the kind of intervention (e.g. the two different provocations described as part of this project each elicit different ethical and social implications), and involve the consideration of issues relevant to both public health and technology use. This project provides a platform for discussing product context differences and how the implications of how and where and why a technology is used could—and should—effect the form it takes and how it operates. We frame our discussion with the challenge of building a body of knowledge across disciplines, particularly in circumstances that require rapid responses to global public health problems, such as COVID-19. Two key considerations arose during the initial discussions that took place with the team in relation to the potential ethical and social implications of the provotype, the first relating to privacy and surveillance, and the second to social equity. While these—and many more—are not independent, we will address these in turn.

4.1 Privacy and Public Health Surveillance

Public health measures are necessary in responding to a pandemic, and various forms of surveillance may also be useful. The World Health Organization (WHO) defines a health measure as "procedures applied to prevent the spread of disease or contamination; a health measure does not include law enforcement or security measures" [55]. Alongside health measures, WHO defines surveillance as "the systematic ongoing collection, collation and analysis of data for public health purposes and the timely dissemination of public health information for assessment and public health response as necessary' [55]. These kinds of approaches may inform activities, such as education, or the implementation of restrictive measures [31]. As described above the COVID-19 pandemic has accelerated the use of a wide range of surveillance technologies, from thermal scanning, contact tracing applications, QR codes and mandatory venue check ins, transport cards to track travel on public transport, the use of drones and even Automated Number Plate Recognition (ANPR) to monitor whether people are within their allowable distance from home. These technologies all collect data and possibly personal information (such as name, geo/location) and raise important ethical, social, and legal concerns especially about privacy.

Privacy is a multifaceted concept that means that aspects of a person's life are private and should not be intruded upon, and that individuals should be able to make informed decisions to be able to control information about them that may be collected, analysed, stored, and shared. Privacy is recognised in numerous international human rights instruments such as the Universal Declaration of Human Rights (UDHR) and the International Covenant on Civil and Political Rights (ICCPR). It is also important to recognise that privacy is not an absolute right, and that incursions into privacy may occur provided that they are proportionate and necessary to achieve a legitimate aim, such as, for example, to protect public health.

It is important to understand the exact contexts in which incursions to privacy through surveillance technology occur, and the types of information that are collected and what is done to/with it (in terms of analysis, sharing, and storage). This needs to be considered with regards to a device that may only display one's temperature to the wearer (for self-monitoring) compared to a device that collects temperature data, analyses it, stores it on servers owned by private companies, and transmits the result of that analysis to state health authorities. In this sense, responsible data management practices should consider both data collection (e.g. scientific justification, and proportionality to the public health threat) and data processing (e.g. quality and security) [26].

There are also related questions about whether an individual can expect to have privacy in public spaces, or in the contexts of employment or private spaces that are used by the public such as shopping centres, restaurants and stadiums (see e.g., [2, 40, 42]). The expectations (and legal protections) that individuals have about their privacy in these various situations and contexts differ due to social norms, and indeed, it has been argued that privacy is contextual [41]. Surveillance itself also shapes the very nature of public space [43]. All of these types of issues must be carefully considered when implementing forms of public health surveillance. The products foreshadowed in the provotoype's in this project will change the power balance in terms of surveillance, as the individual, over an authoritative group or organisation, will have access to, and be in control of, the information about others. The implications of this are a key factor that needs to be resolved and legislated.

4.2 Social Equity

Alongside theoretical risks of public health surveillance interventions, considering potential risks as relevant to real-life settings is essential [31]. By way of example, Klinger and colleagues highlighted the potential for stigmatisation or discrimination resulting from public health surveillance (in particular in relation to published surveillance data); the potential for stigmatisation may be considered from a theoretical perspective, but empirical data and literature (such as considering particular diseases or settings) should be taken into account in order to develop normative responses [31].

Emerging evidence from studies on the range of economic impacts of COVID-19 indicates that those in already at-risk groups may fare worse than others, exacerbating existing social structural inequalities (e.g. [13, 14, 22, 34]. Galasso et al. [17] found that in Italy, one of the developed countries hit hard by COVID-19, those with low levels of education were unlikely to have access to working-from-home adjustments, and that blue collar workers were more likely than white collar workers to work from their regular place of employment [17]. Some people find themselves unable to refuse work in order to prioritise their own and their family's health because to do so would mean financial destitution [33]. A study from Australia found that the mental health of non-health essential workers (e.g. supermarket employees) fared significantly worse than both health essential workers and the general population [44]. They note the importance of paying attention to this 'crucial, but clearly overlooked and vulnerable, group', who also experience poorer job security, less sleep and worse satisfaction in terms of 'specific life domains' including their finances [44].

Studies on low-income workers and their capacity to access sick leave is also relevant to the current study. Swanberg et al. [48] found that the main reason women receiving treatment for breast cancer continued to work their low-income jobs was that they felt they had no financial alternative [48]. Weigt and Solomon [53] found that class partially offset the difficulty faced predominantly by women who were primary carers when negotiating flexible work arrangements, including sick leave, stressing the intersectionality of workplace agency [53].

In this context, the introduction of wearable technology that indicates whether someone is themselves exhibiting physical symptoms that may preclude them from on-site work or service access, may impact differently on already vulnerable portions of society. For example, essential workers who are also low paid may feel less able to stay at home when feeling unwell than those with secure employment and adequate sick leave protections. In other words, they may feel as if they must go to work even when they are unwell in order to meet their financial obligations.

In the event that workplaces mandate the wearing of clothing that indicates a temperature gauge, or some other sign of ill health, precarious workers who are not feeling in perfect health may be precluded from their jobs on the basis of the technology. While this may in fact protect other workers, particularly in contexts where inadequate personal protective equipment (PPE) is available, the financial and mental health implications for low-income workers requires consideration. This is particularly so when considering that these workers tend to be more vulnerable in a variety of intersecting ways, relating to gender, race, disability, and education. These considerations highlight the impact of the implementation of technological solutions on society, particularly during contracted development as is happening during this pandemic. Understanding the implications of a healthcare solution prior to its introduction is key to mitigating against any problems affecting social equity. An interdisciplinary team is needed to ensure an appropriate range of perspectives are integrated into development and implementation.

5 Interdisciplinarity

"We have dismembered reality into a number of disciplines and specialities that, while they may study particular places and cultures, are themselves distinct cultures unto themselves, disconnected from any specific location. The world is, instead, organised spatially, with the knowledge of disciplines all existing in every place, which suggests that in a digitally nomadic future, we would be better served mapping our knowledge virtually and spatially in particular places rather than sorting it into disciplinary classifications" [32].

Incorporating effective and responsible responses to the types of issues raised over the last year has been challenging for researchers, not least because of the siloed nature of tertiary institutions and research facilities where health technologies are often developed [51]. Work that is called 'interdisciplinary' is sometimes comprised of stacking otherwise independent blocks of knowledge next to each other around a shared topic or problem [51]. While we acknowledge the extensive research that has been done in relation to interdisciplinarity [23], particularly in relation to education [7, 54, 58], in the following section we consider the interdisciplinarity of this project from the germinal moment, which was located firmly 'in' engineering. We consider our interdisciplinary team a 'work in progress', as a genuine integration of disciplinary knowledge has to be built over time, from the development of a shared understanding of different disciplinary perspectives, to a shared language. In particular, differences in understanding of the meaning, teaching and application of ethics across engineering and the humanities were found that need to be addressed.

5.1 Broadening Engineering Ethics

In 2008, research by Colby and Sullivan which found that whilst ethics, beyond purely professional ethics, were viewed by engineering departments as core to practice, there was little evidence of it being explicitly integrated into the curriculum [10]. They concluded that case studies were the predominant tool used in individualistic education and that "the broad public purposes and implications of engineering receive relatively little attention in engineering education, aside from the important issues of public safety and environmental sustainability" ([10], p.330).

A few years later, Conlan and Zandvoort [11] called for a broadening of ethics teaching in engineering, "There is a widespread approach to the teaching of ethics to engineering students in which the exclusive focus is on engineers as individual agents and the broader context in which they do their work is ignored" [11]. They argued that engineering graduates were less likely than other graduates to believe they could enact change in society and as a result had a low level of commitment to social action. Conlan and Zandvoort [11] suggested that "in developing educational effort to foster ethical development, it is helpful to think about the goals in broader terms." By 2018, Hess and Fore found that "Promoting the ethical formulation of engineering students through the cultivation of their discipline-specific knowledge, sensitivity, imagination and reasoning skills has become a goal for many engineering education programs throughout the United States." They highlighted six pedagogical strategies for engineering education, involving "…teaching students about professional codes of ethics, humanist readings, reading/discussions on ethical theory, ethical heuristics or decision-making tools, case studies, and service learning" [20], that indicate a maturing of the disciplinary response to the development of technology for society. Mitcham and Englehardt [37] argued for a less isolationist approach, advocating cross-disciplinary collaboration to foster a greater understanding of ethics and the contribution of engineering to human welfare: "Our emphasis is on the need to change the context within which engineers work so that it enables rather than constrains social responsibility" [37].

In professional practice, engineers rarely work alongside sociologists, anthropologists and bioethicists, but arguably they should. Based on his work on addressing complex problems, Harford [19] stressed the importance of cognitive diversity in teams and renewing that cognitive diversity over time as people become used to each other [19]. He pointed out the tendency of people to spend time with people who look and sound similar: "Instead we need to find people or places or situations where we won't be able to avoid new kinds of interactions" [19]. This would benefit society not only because engineering applications would be informed by a broader understanding of their implications also because the social sciences would be informed by the realities of engineering capabilities, both the restrictions and opportunities. By working together in more genuinely integrated practice, from earlier on in a project, different questions could be asked, and potentially different conclusions reached by the team. This is more critical now than at any time in history as the human ability to enact technological change moves beyond the comprehension capabilities of the individual. In the book *Think again: the power of knowing what you don't know*, Grant ([18], 25) urges: "Thinking like a scientist involves more than just reacting with an open mind. It means being actively open minded. It requires searching for reasons why we might be wrong—not for reasons why we must be right—and revising our views on what we learn" [18]. While this seems sound advice, it is easier said than done.

6 Conclusion

In a 'COVID normal' future, with viral threats active in the environment, engineers could develop technologies to allow individuals to detect significantly high temperatures in others, and to signal their own temperature. Yet the form of these technologies and the social and ethical implications need to be considered in order to ensure that potential protections do not perversely undermine social coherence, individual rights, and the defence of the potentially vulnerable in society.

The practical subject of this pilot is applications of technologies that enable the detection of body temperature in a public or private (i.e., business) setting and the development of recommendations on forming teams for this type of pandemic response. The intent behind using such applications has been to identify whether a person may or may not be infectious with COVID-19. Technologically, this is relatively straight forward, but both ethically and sociologically, it is more complex. While by no means conclusive, body temperature was quickly introduced as a screening measure in 2020 at airports and in shopping centres, medical practices etc. Entry to otherwise public venues became conditional on a 'normal' level temperature check. These were conducted using hand-held devices directed at the forehead of the individual and manned by essentially untrained staff members across a myriad of business operations and public buildings. However, there are always implications for society and the individual in the development of healthcare technology solutions. In the current pandemic the rush to provide technological solutions to the crisis needs need to be tempered by research by integrated research across many disciplines science and the humanities. While the tensions involved in this approach are not new, the case studies available during this time are. By studying these examples from a deliberately interdisciplinary standpoint, society could be better prepared for future pandemics—and other crisis situations where these is a risk that technological determinism could create unexpected consequences for society if not well thought through. Lessons from this pandemic will form the basis for responses to the next one. It is imperative to critically question whether we have enough effective collaboration across the research domains of science and society. It is key that collaborations across the two spheres are not swept away with the need for the rapid response and deployment of technological 'solutions' that may unwittingly embed and exacerbate long-term social issues. In building future preparedness, it would benefit society if the social and ethical implications of technological innovation were understood and counted in real time as part of a transition research approach, rather than studied historically once unexpected consequences emerge.

Technological innovation detached from social, philosophical and ethical sociological perspectives is a problematic practice both from the point of view of development informed by context, and from a creativity point of view, as design in context provides opportunities for innovative thinking that are inspired by designing at a particular point in time. In discussing this specific example at this time, this chapter makes a contribution to knowledge about provides an unusual view in questioning how to model practice that combines technological innovation strategies while considering social implications and social science perspectives and sociological innovation strategies in that it is informed in real time by rapidly unfolding world developments. Essentially the discussion adds another chapter to the technological question, if it is possible to do, who makes decisions on whether it should be done and it part of the ongoing dialogue on doing the importance of investing in doing the right thing (for society), before focussing on doing it right (technologically).

The evolution of healthcare technology has undergone radical acceleration and redirection over the last year in response to the COVID-19 pandemic. The pace of technological and social change is unlikely to dimmish over the next few years as digital convergence drives exponential growth and COVID-19 beaks the shackles of conventional thinking. Yet for engineers, healthcare providers and sociologists to actually exploit emerging technological capabilities for the benefit of society, there needs to be an equally radical revision of thinking in the way disciplinary expertise is combined. Conventional, linear collaborative practices need to be replaced with genuinely integrated science and humanities. This will not happen without a concerted approach to inculcating new ways of thinking, new ways of working. Cognitive flexibility, respect for different realms of expertise and new ways of working need to be established, and quickly.

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References

1. Adams, S., Bucknall, T., Kouzani, A.: A study on the agreement of body temperatures measured by infrared cameras and oral thermometry (2020)
2. Bernstein, E.B.: Health Privacy in Public Spaces. Ala. L. Rev. **66,** 989 (2014)
3. Block, I.: Guardian G-Volt masks would use graphene and electrical charge to repel viruses and bacteria. de zeen (2020a). https://www.dezeen.com/2020/03/06/guardian-g-volt-face-mask-graphene-coronavirus-bacteria/. Accessed 28 June 2021
4. Block, I.: Pharrell Williams partners with Pentatonic to create coronavirus cutlery set (2020b). https://www.dezeen.com/2020/07/04/pharrell-williams-pentatonic-pebble-coronavirus-sustainable-cutlery/. Accessed 28 June 2021
5. Block, I.: Christophe Gernigon proposes suspended Plex'eat hoods for post-virus dining in restaurants. de zeen (2021). https://www.dezeen.com/2020/05/22/christophe-gernigon-plex-eat-coronavirus-face-shield-dining-design/. Accessed 28 June 2021
6. Carr, N.: To save everything click here: technology, solutionism and the urge to fix problems that don't exist. Nature **495,** 45–45 (2013)
7. Casey, A., Jones, B.: Using digital technology to enhance student engagement in physical education. Asia-Pac. J. Health, Sport. Phys. Educ. **2**, 51–66 (2011)
8. Catching, A., Capponi, S., Te Yeh, M., Bianco, S., Andino, R.: Examining the interplay between face mask usage, asymptomatic transmission, and social distancing on the spread of COVID-19. *medRxiv* (2020)
9. Ciani, O., Armeni, P., Boscolo, P.R., Cavazza, M., Jommi, C., Tarricone, R.: De innovatione: the concept of innovation for medical technologies and its implications for healthcare policy-making. Health Policy Technol. **5**, 47–64 (2016)
10. Colby, A., Sullivan, W.M.: Ethics teaching in undergraduate engineering education. J. Eng. Educ. **97**, 327–338 (2008)
11. Conlon, E., Zandvoort, H.: Broadening ethics teaching in engineering: Beyond the individualistic approach. Sci. Eng. Ethics **17**, 217–232 (2011)
12. den Hartog, G., van Binnendijk, R., Buisman, A.-M., Berbers, G.A., van der Klis, F.R.: Immune surveillance for vaccine-preventable diseases. Expert Rev. Vaccines **19**, 327–339 (2020)
13. Dubowitz, T., Dastidar, M.G., Troxel, W.M., Beckman, R., Nugroho, A., Siddiqi, S., Cantor, J., Baird, M., Richardson, A.S., Hunter, G.P.: Food insecurity in a low-income, predominantly African American cohort following the COVID-19 pandemic. Am. J. Public Health **111**, 494–497 (2021)

14. Egede, L.E., Walker, R.J.: Structural racism, social risk factors, and Covid-19—a dangerous convergence for Black Americans. N. Engl. J. Med. **383**, e77 (2020)
15. Escobedo, P., Bhattacharjee, M., Nikbakhtnasrabadi, F., Dahiya, R.: Smart bandage with wireless strain and temperature sensors and battery-less NFC tag. IEEE Internet Things J. (2020)
16. Feinhandler, I., Cilento, B., Beauvais, B., Harrop, J., Fulton, L.: Predictors of death rate during the COVID-19 pandemic. Healthcare 339 (2020). Multidisciplinary Digital Publishing Institute
17. Galasso, V., Pons, V., Profeta, P., Becher, M., Brouard, S., Foucault, M.: Gender differences in COVID-19 attitudes and behavior: panel evidence from eight countries. Proc. Natl. Acad. Sci. **117**, 27285–27291 (2020)
18. Grant, A.: Think Again: The Power of Knowing What You Don't Know. Viking (2021)
19. Harford, T.: Messy: How to be Creative and Resilient in a Tidy-Minded World. Hachette UK (2016)
20. Hess, J.L., Fore, G.: A systematic literature review of US engineering ethics interventions. Sci. Eng. Ethics **24**, 551–583 (2018)
21. Hewlett, A.L., Kalil, A.C., Strum, R.A., Zeger, W.G., Smith, P.W.: Evaluation of an infrared thermal detection system for fever recognition during the H1N1 influenza pandemic. Infect. Control Hosp. Epidemiol. **32**, 504–506 (2011)
22. Hibel, L.C., Boyer, C.J., Buhler-Wassmann, A.C., Shaw, B.J.: The psychological and economic toll of the COVID-19 pandemic on Latina mothers in primarily low-income essential worker families. Traumatology (2021)
23. Horn, M.J., Nickols, S.Y.: Interdisciplinary research: Have we lost our focus? Home Econ. Res. J. **11**, 9–14 (1982)
24. Howard, N.: ABC News masks. US protesters including young children burn face masks at Idaho Capitol rally against coronavirus measures. ABC News (2021). https://mobile.abc.net.au/news/2021-03-07/protesters-burn-masks-at-idaho-capitol-rally-against-rules-us/13224588. Accessed
25. Hu, X., Gao, J., Luo, X., Feng, L., Liu, W., Chen, J., Benachi, A., De Luca, D., Chen, L.: Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) vertical transmission in neonates born to mothers with coronavirus disease 2019 (COVID-19) pneumonia. Obstet. Gynecol. (2020)
26. Ienca, M., Vayena, E.: On the responsible use of digital data to tackle the COVID-19 pandemic. Nat. Med. **26**, 463–464 (2020)
27. INGRID JOHNSTON, P.: Australia's public health response to COVID-19: what have we done, and where to from here? Aust. N. Z. J. Public Health **44**, 440 (2020)
28. Islam, M.M., Mahmud, S., Muhammad, L., Islam, M.R., Nooruddin, S., Ayon, S.I.: Wearable technology to assist the patients infected with novel coronavirus (COVID-19). SN Comput. Sci. **1**, 1–9 (2020)
29. Jeong, H., Rogers, J.A., Xu, S.: Continuous on-body sensing for the COVID-19 pandemic: gaps and opportunities. Sci. Adv. **6,** eabd4794 (2020)
30. Khan, S., Saultry, B., Adams, S., Kouzani, A.Z., Decker, K., Digby, R., Bucknall, T.: Comparative accuracy testing of non-contact infrared thermometers and temporal artery thermometers in an adult hospital setting. Am. J. Infect. Control **49**, 597–602 (2021)
31. Klingler, C., Silva, D.S., Schuermann, C., Reis, A.A., Saxena, A., Strech, D.: Ethical issues in public health surveillance: a systematic qualitative review. BMC Public Health **17**, 1–13 (2017)
32. Kolarevic, B., Duarte, J.P.: Mass customization and design democratization. Routledge (2018)
33. Lancet, T.: COVID-19: protecting health-care workers. Lancet (London, England) **395,** 922 (2020)
34. Leira, E.C., Russman, A.N., Biller, J., Brown, D.L., Bushnell, C.D., Caso, V., Chamorro, A., Creutzfeldt, C.J., Cruz-Flores, S., Elkind, M.S.: Preserving stroke care during the COVID-19 pandemic: potential issues and solutions. Neurology **95**, 124–133 (2020)
35. Madowo, L.: We Don't Live in a Communist Country!': battle over masks rages in Texas. Guardian (2020). https://www.theguardian.com/us-news/2020/jul/02/texas-masks-coronavirus-covid-battle. Accessed 23 May 2021

36. Meier, K., Glatz, T., Guijt, M.C., Piccininni, M., Van Der Meulen, M., Atmar, K., Jolink, A.-T.C., Kurth, T., Rohmann, J.L., Zamanipoor Najafabadi, A.H.: Public perspectives on protective measures during the COVID-19 pandemic in the Netherlands, Germany and Italy: A survey study. PloS one **15,** e0236917 (2020)
37. Mitcham, C., Englehardt, E.E.: Ethics across the curriculum: Prospects for broader (and deeper) teaching and learning in research and engineering ethics. Sci. Eng. Ethics **25**, 1735–1762 (2019)
38. Morozov, E.: The tech 'solutions' for coronavirus take the surveillance state to the next level. The Guardian 25 (2020)
39. Network, S.A.S.: Funding Opportunities. Deakin University (2021). https://scienceandsocietynetwork.deakin.edu.au/funding-opportunities/. Accessed 28 June 2021
40. Nissenbaum, H.: Toward an approach to privacy in public: Challenges of information technology. Ethics Behavior **7,** 207–219 (1997)
41. Nissenbaum, H.: Privacy in Context. Stanford University Press, Palo Alto. CA (2009)
42. Paton-Simpson, E.: Privacy and the reasonable paranoid: the protection of privacy in public places. Univ. Tor. Law J. **50,** 305–346 (2000)
43. Patton, J.W.: Protecting privacy in public? Surveillance technologies and the value of public places. Ethics Inf. Technol. **2,** 181–187 (2000)
44. Rossell, S.L., Neill, E., Phillipou, A., Tan, E.J., Toh, W.L., van Rheenen, T.E., Meyer, D.: An overview of current mental health in the general population of Australia during the COVID-19 pandemic: results from the COLLATE project. Psychiatry Res. **296**, 113660 (2021)
45. Scheidel, W.: The Great Leveler: Violence and the History of Inequality from the Stone Age to the Twenty-First Century. Princeton University Press (2018)
46. Struyf, T., Deeks, J.J., Dinnes, J., Takwoingi, Y., Davenport, C., Leeflang, M.M., Spijker, R., Hooft, L., Emperador, D., Dittrich, S.: Signs and symptoms to determine if a patient presenting in primary care or hospital outpatient settings has COVID-19 disease. Cochrane Database of Systematic Reviews (2020)
47. Sugathan, A., Roy, G.G., Kirthyvijay, G., Thomson, J.: Application of Arduino based platform for wearable health monitoring system. In: 2013 IEEE 1st International Conference on Condition Assessment Techniques in Electrical Systems (CATCON), pp. 1–5. IEEE (2013)
48. Swanberg, J.E., Nichols, H.M., Ko, J., Tracy, J.K., Vanderpool, R.C.: Managing cancer and employment: Decisions and strategies used by breast cancer survivors employed in low-wage jobs. J. Psychosoc. Oncol. **35**, 180–201 (2017)
49. Taylor, J.: Coronavirus app: will Australians trust a government with a history of tech fails and data breaches? Guardian (2020). https://www.theguardian.com/australia-news/2020/apr/26/coronavirus-app-will-australians-trust-a-government-with-a-history-of-tech-fails-and-data-breaches. Accessed 4 May 2021
50. Trottier, D., Huang, Q., Gabdulhakov, R.: Covidiots as global acceleration of local surveillance practices. Surveill. Soc. **19**, 109–113 (2021)
51. Walker, M.J., Goddard, E., Stephens-Fripp, B., Alici, G.: Towards including end-users in the design of prosthetic hands: ethical analysis of a survey of Australians with upper-limb difference. Sci. Eng. Ethics 1–27 (2019)
52. Watts, D.: Covidsafe, Australia's digital contact tracing app: the legal issues. Australia's Digital Contact Tracing App: The Legal Issues (2020)
53. Weigt, J.M., Solomon, C.R.: Work–family management among low-wage service workers and assistant professors in the USA: a comparative intersectional analysis. Gend. Work. Organ. **15**, 621–649 (2008)
54. Welch, D., Loy, J.: A brave new creativity. Art Des. Commun. High. Educ. **12**, 91–102 (2013)
55. WHO: International Health Regulations (2005) 3rd edn. The World Health Organisation (2016). https://www.who.int/publications/i/item/9789241580496. Accessed 28 June 2021

56. Winner, L.: Do artifacts have politics? Routledge (2017)
57. Wouters, O.J., Shadlen, K.C., Salcher-Konrad, M., Pollard, A.J., Larson, H.J., Teerawattananon, Y., Jit, M.: Challenges in ensuring global access to COVID-19 vaccines: production, affordability, allocation, and deployment. Lancet (2021)
58. Zeidmane, A., Cernajeva, S.: Interdisciplinary approach in engineering education. In: 2011 IEEE Global Engineering Education Conference (EDUCON), pp. 1096–1101. IEEE (2011)

Decision-Making Analytics for COVID-19

EMD and Horizontal Visibility Graph Based Disease Tagging for Covid-Positive Chest Radiographs

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Abstract This work describes preliminary steps in the ongoing implementation of horizontal visibility graphs (HVG) and related Hamming-Ipsen-Mikhailov (HIM) network similarity (distance) metric to provide automatic disease tag for normal and COVID-positive chest radiographs. A detailed exploration in transformation of a normal or COVID positive chest radiograph to a horizontal visibility graph and its network/graph-theoretic analysis and visualization in R computational environment is presented. Further, HIM network similarity metric is illustrated and its usage in generating automatic disease tag based on test radiograph's HIM-distance from healthy and COVID positive representative radiographs is presented. Finally, statistically success rate of 60% is observed despite of low quality and mismatched (Normal and COVID positive radiographs are not from same patients) using HVG–HIM and 30% using EMD, which augurs well for the development of this system as a quick disease tag device. Difference in drastic performance is owing to serious computational investment in HVG–HIM. A webservice based portal for automated diseases tagging of chest radiograph is proposed, built and illustrated to take basic clinical services to the poorest of the poor in the LMICs and in African countries. It can be used by primary health care centers (PHCs) for a first aid scan and then patient can be referred to specialists. On a macro scale where patients overwhelm medical

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facilities due to astronomical numbers involved, this kind of system can relieve the suffering of humanity to some extent. We also reflect on our programmatic and static computational approach as compared to nonlinear dynamical and often unstable, energy-hogging deep learning.

Keywords COVID-29 · Earth Mover's Distance (EMD) · Horizontal visibility graphs (HVG) · Chest radio-graphs

1 Introduction

As the healthcare systems across the world grapple with the grim realities of changed landscape of disease burden in the post-covid era, it is becoming imperative to develop fruganomic healthcare technologies capable of gathering evidence from the community to augment the hospital based registries in providing reasonably accurate estimates of the disease burden which will definitely help the health policy administrators to get a unequivocal narrative in a nuanced manner to develop niche specific disease surveillance and forecasting systems. This will indeed help the Healthcare administrators to develop and deploy novel, affordable and more importantly accessible instruments such as policies and programmes aimed at evaluating the health status of the community at large particularly in resource limited healthcare systems prevalent in low-and lower-middle-income countries (LLMICs) such as the Indian sub-continent. India endowed with unique geological relief structures and divergent genetic base provides a unique landscape of disease burden necessitating the need to develop tools capable of being ported into mobile platforms (iOS/HTC/Android), since mobiles have a good penetration in the rural milieus of the Indian sub-continent. This is further compounded by the fact that Non-communicable Diseases (NCDs) disproportionately affect people living LLMICs [1–3], accounting for three quarters of the mortalities within LLMICs [4]. The relationship among NCDs, poverty, social and economic development [5], is likely to pose a major challenge to development as well as attainment of Sustainable Development Goals (SDGs) by 2030 [6, 7]. The marginalized sections of the society in LLMICs are vulnerable to NCDs for many reasons, including socio-economic constraints, psychosocial stress, higher levels of risk behavior, unhealthy living conditions, limited access to high-quality health care along with reduced opportunity to prevent complications. The prevalence of unhealthy risk behaviors such as consumption of tobacco and alcohol products along with sedentary lifestyle will make these population vulnerable to the ravages of "NCD Epidemic" which has been hitherto underacknowledged and unaddressed until the advent of COVID pandemic. The fact that India is projected to experience more deaths from NCDs than any other country over the next decade, primarily due to the size of the population and worsening risk factor profile will significantly impact economic growth. The deeply entrenched social and economic disparities, with lack of affordable and accessible healthcare presents a pre-emptive scenario for the emergence of several epidemics/ pandemics such as COVID-19 with devastating consequences.

In the last two decades, the translation of the fundamental concepts of precision medicine at a community level to understand the patterns and processes associated with the landscape of disease burden in the LLMICs having fractious and fractionated health-care ecosystems such as the Indian sub-continent necessitates the need to develop novel, cutting edge, and disruptive fruganomic community empowering solutions aimed alleviating the healthcare disparities. In the last two decades India has witnessed an epidemiological transition from communicable diseases to NCDs in the last two decades with cardiovascular diseases and Cancer accounting for a significant proportion of morbidities and mortalities, the un-finished agenda of communicable diseases has led to emergence of recent pandemics such as COVID-19 [8–10]. Although the World Health Organization (WHO) has recognized the outbreak of COVID-19 in January 2020 and declared it as a pandemic in March 2020, the statutory impact on the economy of all the countries including India has clearly affected the health outcomes of the populace belonging to the weaker socio-economic strata.

COVID-19 associated co-morbidity was observed in patients who had underlying risk factors of hypertension, diabetes, and chronic respiratory problems. Chronic respiratory problems account for 8% of the mortalities and India has 18% of the global population with an ever-increasing burden of chronic respiratory diseases including chronic obstructive pulmonary disease (COPD), asthma, pneumoconiosis, interstitial lung diseases, and pulmonary sarcoidosis [11–13]. Environmental factors such as air pollution, water pollution, and soil pollution to name a few are known to significantly contribute to premature mortality and disease burden globally, with the highest impact in low-income and middle-income countries such as the Indian subcontinent endowed with resource limited healthcare systems [14, 15].

Recent evidences suggest that use of multi-modal multi sensor fusion technologies along with big data enabled platform, would significantly contribute towards the strengthening resource-deprived healthcare systems prevalent in the Indian subcontinent. The technology (artificial intelligence AI) enabled transition of precision medicine to precision public health must be integrated into the existing framework of healthcare systems with a view administer the provision of affordable and accessible healthcare solutions intrinsic to the niche specific needs of LLMICs. The integration of the disruptive and cutting-edge healthcare solutions within the framework of the existing healthcare systems will significantly improve the health outcomes of the community at large.

A major drawback of the existing interpretation algorithms based on Artificial Neural Networks (ANN) is its black-box nature, which coupled with increased computational complexity leads to increased carbon foot-printing and thereby global warming [16, 17] but solutions are also emerging [18]. Apart from this, the process of obtaining a result is also difficult to understand as to why and how it arrived at the answer [19–21]. Further, the nonlinear dynamical behavior of deep neural networks is prone to chaotic nature and fundamental underlying unpredictability [22–24]. On the other hand, static and predictable algorithms like, Earth Movers

Distance (EMDs) and Visibility Graph perform image match by computing perceptual similarity and provide more meaningful and interpretable solutions to matching problems. Taken together, ANNs have a long and very well researched history of inherent instability and its auto-mated decisions can't be entrusted to make decisions critical to the survival of a patient afflicted with a severe case of a COVID-19 lung ailment [25–28].

Chest radiographs are still most common modality for diagnosing lung disease conditions and the development of tools and applications that can seamlessly evaluate lung health of LMICs such as India will significantly augment healthcare outcomes. Additionally, the lack of well-structured databases for referencing and analysis hinders the progression of research from aiding and optimizing processes and clinical decision making with the help of Artificial Intelligence (AI) [29, 30].

India endowed with diverse genetic base and socio-cultural norms, presents a unique landscape of disease burden necessitating the need for niche specific databases for enhancing the accuracy of AI-enabled tools. The socioeconomic impact and benefits of AI based automation of Chest Radiograph analysis for LMICs like India will significantly improve the clinical outcomes of patients afflicted with lung diseases and outweigh the challenges leading to its integration to the existing framework of the healthcare system [31, 23]. The potential application of AI-enabled platforms would provide a valuable, precision public health tool for better management of lung disease epidemic by improving the clinical outcomes thereby alleviating a significant burden on the national health spend.

The fundamental impact of integrating smart clinical devices, IoT, and Industry 4.0 with clinical software and closed-loop resource allocation is the ability to rapidly deploy medical infrastructure in challenging places during natural calamities like flood, earthquake, drought, Tsunamis etc., while drastically reducing costs and reacting to demands in patients' preferences, pharma industry changes, the supply chain, and technology upgrades.

Broadly, this work makes following contributions in moving towards clinical dis-ease tagging as a webservice:

- This work describes a natural approach for automated Covid positive chest radiograph tagging using computational ideas like perceptual similarity, Earth Mover's Distance (EMD) and converting the chest radiographs into a network/graph using horizontal visibility graph procedure and then computing similarity scores by HIM network distance metric. From all perspectives, it is a first work of its kind whose time has arrived due to Covid clinical and hence socio-economic emergency.
- This disease tagging is being presented as an app on any mobile platform of choice where all user/patient/doctor/medical professional must do is to upload their Covid chest radiograph and system will generate disease tag. This is possible due to advent of affordable smartphone technology and its accessibility across socio-economic spectrums.
- Same algorithmic ideas with intense computational engine are interfaced as web service, where disease tagging can be done in large batches since one of the major issues in Covid waves, large numbers of people getting infected in a very short

time span. These is a clear need for such a system which can cope up with this kind of Covid-infection load in an agile fashion.

Rest of this chapter is organized as follows: Sect. 2 discusses related work in the context of HVG. Section 3 describes clinical and public health motivations behind deploying this technology. Section 4 presents basic mathematical definition of EMD. Section 5 describes HVG, HIM and related results. Section 6 illustrates different levels of processing in HVG for Covid positive chest radiographs. Section 7 reports on computational results from HVG–HIM implementation on chest radiographs for disease tagging. Section 8 demonstrates our basic implementations as a webservice for remote accessibilities in LMICs. Finally, Sect. 9 collects our insights and experiences in conclusion and suggests future directions for development.

2 Related Work

Motivation behind visibility graph generation was to develop simple and fast computational methods, which transform a time series into a network or a graph. This resulting visibility graph in turn inherits multiple features of the original timeseries in its spatial organization. For example, periodic timeseries transform into regular graphs, and random timeseries manifest themselves random graphs [32, 33]. Along these lines, horizontal visibility algorithm, a geometrically more intuitive and analytically tractable version of visibility graph algorithm, focusing on the transformation of timeseries into graphs [34], has been proposed. It turns out that, exact results on the topological properties of these horizontal visibility graphs, like, the degree distribution, the clustering coefficient, and the mean path length, can be obtained. The horizontal visibility algorithm can also be used as an intuitive method to discern between any two different timeseries. It is precisely this capability we leverage here to automatically categorize normal and Covid positive chest radiographs. HVG along with features like mean node degree and degree distribution has been used to categorize the sleep stages based on graph domain properties from a single-channel electroencephalogram (EEG) signal [17, 35].

Visibility graph methods have been found effective in describing the fractal properties of Geophysical time series [36]. The understanding of various graph-theoretical metrics pertaining to visibility graphs, their interdependent nature, and their sensitivity with respect to missing values and randomness are explored. Visibility graph algorithms have been applied to fMRI time series to simultaneously compute and process relevant dimensions of both local and global dynamics in a natural fashion, and to explore a transformation between time series and network theory in the context of network neuroscience [37]. It has been illustrated that the network architecture of the image visibility graphs represents important information on the organization of the image from which they are derived and potentially they can make good image filters [38]. Using HVG, a general class of predictors, which can be deployed to augment existing properties used in heart rate variability (HRV) analysis, and which show high predictive power for multiple cardiovascular diseases, have been defined and validated [39]. Normalized weight vertical visibility algorithm (NWVVA) has been proposed to extract EMG-based features for myopathy and ALS detection [40]. In this algorithm, sampling points or nodes based on sampling theory are derived, and features are computed based on interrelations among the vertical visibility nodes with their amplitude differences as weights. The similarity graph algorithm are used to analyze the time series of motor activity, extracted from actigraph registrations over 12 days in depressed and schizophrenic patients. These were mapped into a graph and then techniques from graph theory were applied to describe these time series, searching for variations in complexity [41].

Visibility graph methods were deployed to analyze ECoG signals in rats [42]. Subsequently, typical metrics in network science (graph properties) were applied to compute network properties of topological structure of these graphs derived from ECoG signals. A family of Feigenbaum graphs, which are horizontal visibility graphs (HVGs) generated from the trajectories of one-parameter unimodal maps undergoing a period-doubling route to chaos (Feigenbaum scenario), have been analyzed [43]. It has been found that while the maximum eigenvalue of HVG can easily discern chaos from a white noise process, it is not a good metric to quantify the chaoticity of the process, and that the eigenvalue density is perhaps a better indicator for the same.

3 Motivation for Building This Tool and Methodology

This work is motivated by following two objectives.

1. Development and validation of an Intelligent Decision Support System for segregating Chest Radiographs to detect COVID-19 associated lung diseases in both tertiary care settings and extended community along with tracking of patients through low end mobile health applications [44–46].
2. Integration and validation of multi-modal tool in clinical practice involving automated processing of anonymized chest radiographs along with conventional molecular biomarkers [47, 48] of tissue hypoxia in both angiogenic and fibrotic phases of the lung disease progression forming the rationale of effective triage methods for prioritizing the most urgent conditions to wait listed ones.

The race and sex-specific variations in the levels of conventional biomarkers such as Angiogenesis/Fibrosis indeed necessitate the validation and confirmation by a non-invasive AI-enabled modality, which can seamlessly crunch a large amount of data in an affordable and accessible manner. Our fruganomic data intensive AI-enabled tool will not only facilitate the same by incorporating the clinical-epidemiological features of the subjects evaluated at tertiary care centers and the extended community but also upon integration with the digital signals from surrogate molecular markers will result in the creation of a multi-modal multi fusion sensor technology [27, 29, 30] which will aim at not only resolving the dogma of missed and misdiagnosis of Lung diseases such as Tuberculosis or Pneumonia at tertiary care centers and extended community but also individualize the risk assessment of patients with suspected myocardial infarction or to categorize patients into low- or high-risk groups.

In Recent years, various computer-based tools have been developed which can be reliably used for computational disease tagging purposes. Healthcare Professionals with the help of such tools can accurately and computationally tag different disease conditions within a short time with a view to significantly improve the health outcomes of the community at large [49–57].

In the past people have prospected the use of deep learning models with limited efficiency to diagnose lung diseases which use X-ray images as a modality to evaluate lung health as well as predict the onset of diseases such as Covid-19 in the patients [31]. In this paper, we have explored the possibility to predict the lung ailment by applying Earth mover's Distance algorithm [58, 59] as our ongoing work along with Visibility Graph to the X-Ray images of the patients. EMD mimics the human perception of texture similarity whilst Horizontal visibility graph (HVG) and Hamming-Ipsen-Mikhailov (HIM) distance-based similarity approach forms a corner stone for automatically distinguishing clinical multimedia in an automated fashion. This stable and programmatic algorithmic capability can be leveraged to provide automated disease tagging where highly trained medical professional services are either too scarce or unaffordable. These observations when coupled together form the rationale for scalable automated clinical disease tagging for community-oriented health intervention.

3.1 Earthmover's Distance (EMD)

Earthmover's Distance (EMD) is a method to calculate the disparity between two multi-dimensional distribution in some space where a distance magnitude between single ones (ground distance) is given. Suppose the two distributions are there, one can be considered as the area with the mass of earth, and the other as a collection of holes in that same area. Then, the EMD is the measure of the least amount of work required to fill the holes with earth. Here the unit of work is the force needed in transporting unit earth by a unit of ground distance. So, it can also be defined as the minimum cost that must be provided to convert one histogram into other. Measuring of EMD is based on a solution of transportation problem [16]. For finding mathematical representation, firstly we formalized it as the following linear programming problem:

Let X be the first signature with n clusters, xi is the cluster representative, and wxi is the weight of cluster.

Let Y be the second signature with m clusters, yi is the cluster representative, and wyi is the weight of cluster.

Let D be the ground distance matrix, di j is the ground distance between clusters xi and y j.

Let F be the flow matrix and fi j is the between xi and y j.

Then,

$$X = \{(x_1, w_{x1}), (x_2, w_{x2}), (x_3, w_{x3}), \ldots(x_n, w_{xn})\}$$

$$Y = \{\left(y_1, w_{y1}\right), \left(y_2, w_{y2}\right), \left(y_3, w_{y3}\right), \ldots\left(y_m, w_{ym}\right)\}$$

$$D = \left[d_{ij}\right]$$

$$F = \left[f_{ij}\right]$$

Now, the WORK (X, Y, F) = $\sum_{i=1}^{n}\sum_{i=1}^{m} f_{ij}d_{ij}$ Subject to constraints: (i) $f_{ij} \geq 0$, where $0 \leq i \leq n$, $0 \leq j \leq m$; (ii) $\sum_{j=1}^{m} f_{ij} \leq w_{xi}$, where $0 \leq i \leq n$; (iii) $\sum_{j=1}^{m} f_{ij} \leq w_{yj}$, where $0 \leq j \leq m$; (iv) $\sum_{i=1}^{n}\sum_{i=1}^{m} f_{ij} = \min \sum_{i=1}^{n} w_{xi}.\sum_{j=1}^{m} w_{yi}$ The constraint (i) enables mass moving from X to Y. (ii) and (iii) restricts the amount of mass that can be sent by the clusters in X to their weights and the clusters in Y to receive no more mass than their weights. (iv) One forces to move the maximum amount of mass possible. It is also known as the total flow. Once we solve the transportation problem, we will get the optimal flow F. Now the Earth Mover's Distance is defined as the work normalised by the total flow:

$$EMD(X, Y) = \sum_{i=1}^{n}\sum_{j=1}^{m} f_{ij}d_{ij} \div \sum_{i=1}^{n}\sum_{j=1}^{m} f_{ij}$$

3.2 *Horizontal Visibility Graph (HVG) and Its Application for X-ray Chest Radiograph Processing in R*

The notion of visibility says that if two data points in a time series are in the line of sight without being obstructed by any other data points then they are visibible and hence they are connected in a visibility graph. This tranformation by visibility gives rise to the mapping of a timeseries into a network as per given specific geometric condition which is outlined below. Any two given data points (t1, i1) and (t2, i2) from timeseries obtained from covid or normal X-ray image matrix time series will be said to be visible and hence connected in the ensuing graph if for any other data point (t3, i3), for all t1 < t3 < t2 satisfies.

$$\mathrm{i3} < \mathrm{i1} + (\mathrm{i2} - \mathrm{i1})$$

$$\mathrm{tc} - \mathrm{t1}$$

$$t2 - t1$$

What it essentially means that all values yi for all t1 < ti < t2 should stay below the line drawn between i1 and i2. Limiting this notion of visibility to only horizontal direction, one can intuitively understand the notion of horizontal visibility where two data points are horizontally visible if one can draw a horizontal line between them or establish a line of sight while all other values between these two data points are staying below this line: ii, il > ik for all k such that j < k < l [33]. Clearly, as in the visibility case, horizontal visibility algorithm maps a sequence of data points/timeseries to a horizontal visibility graph (HVG). Once, HVG representation is obtained, massive analytic capabilities of network analysis and tools of network science and graph theory can be deployed to analyze the original sequence of datapoints combinatorically, resulting in hitherto unknown criteria for data sequence characterization. While there are large number of visibility graph applications in multiple multidisciplinary areas, this work leverages this method for classifying and distinguishing patients with a certain pathology from healthy controls, by using the network attributes of HVGs as feature-vectors for automatic disease-tagging. In particular, an analysis of automation classification of healthy and corona-positive patients is presented with digital lung-Xray modality [34].

3.2.1 Hamming-Ipsen-Mikhailov (HIM) and Network Similarity Metric

Hamming distance is a simple metric which computes the number of slots where two strings of equal length differ [60]. Alternatively, it counts the number of edits or substitutions required to transform one representation into the other. Generally speaking, its edit distance between two strings and can be deployed as a local metric to compute two networks' similarity indices. Ipsen-Mikhailov distance was pioneered by Ipsen [61] for graph reconstruction problems. Jurman et.al. [62] expanded its usage to "graph-comparison" methods.

The Ipsen-Mikhailov (IM) distance is a spectral measure which models a topology of N molecules connected by flexible springs. These network topologies are organized by the underlying adjacency matrix. The global (spectral) metric IM is the Ipsen-Mikhailov distance pertaining to the square-root of the squared difference of the Laplacian spectrum for each graph. The Ipsen-Mikhailov distance outlines the difference between two graphs by comparing their respective spectral densities and not by the raw eigenvalues themselves.

To take the advantage of local nature of Hamming and global nature of IM, the Hamming-Ipsen-Mikhailov distance is proposed. It is is a weighted combination of the Ipsen-Mikhailov (IM) and the normalized Hamming (H). The Hamming-Ipsen Mikhailov (HIM) distance is an Euclidean metric on the space created by the Cartesian product of the metric space associated with H and IM. The contributions of global and local information is governed by a combination factor ξ used in the formula. When ξ is one, local and global information are in balance; when ξ is tending to 0, it becomes (local) Hamming distance; and when it goes to ∞ it resembles the (global) Ipsen Mikhailov distance.

$$d_{HIM} = \frac{1}{\sqrt{1+\xi}}\sqrt{\xi IM^2 + H^2}$$

Like mentioned earlier, this distance benefits from the strengths of both the Hamming and the Ipsen-Mikhailov distances by leveraging local and global information. Further, since it combines two distances with a non-negative weight, it defines a proper network distance between graphs. The parameter ξ gives the control to the metric by letting the user favor one type of information over the other. However, empirically, it is well observed that this distance is computationally expensive, and thus costly to apply to the analysis of massive graphs and large datasets. For our purposes here, HIM distance is used to compare two horizontal visibility graphs (HVG) which are generated either from normal or covid positive x-ray radiographs. The ensuing network similarity helps us decide the appropriate disease tag as will be demonstrated in the computational results.

4 Dataset

Primary source of normal and Covid-positive chest radiographs have been sourced from Rajiv Gandhi Cancer Institute and Research Centre [63] where representative normal and unhealthy ECGs, were compared *Diseasetagging with Visibility Graph and EMD based analysis of training data.*

With the given 100 test ECGs. Similar process has been followed for Covid-positive disease tagging using EMD with 30% success rate. Following similar reasoning, if test chest radiograph is closer to normal radiograph i.e. its VG-HIM distance is smaller to normal one, then it is tagged as a normal chest radiograph and if it resembles Covid positive chest radiograph, i.e. its VG-HIM distance is small with respect to representative Covid positive chest radiograph, then it is tagged as a Covid positive chest radiograph as shown in Table 3 next. A success rate of 60% for HVG–HIM based disease tagging has been reported. The full process has been shown as a flowchart in Fig. 13. We compute that our success rate is 60 out of hundred or 60% which calls for multimodality and that is where biomarkers [47, 48] walk in as a natural basis of Covid positive classification to further enhance the automated tagging of Covid positive chest radiographs with enhanced confidence.

4.1 *Transformation of a Chest Radiograph to a Horizontal Visibility Graph: Different Stage of Processing*

To illustrate the complete process from starting with a chest radiograph to generating its horizontal visibility graph to get it ready for HIM distance computation is accomplished in multiple different computational processing stages. We are going to illustrate it using COVID positive training image, COVID Train7.jpeg as shown in Fig. 1. We can notice that compared with a normal chest radiograph it has more white cloud like structures which possibly might be due to Covid positive nature of the radiograph. To process it, chest radiograph is converted to a down sampled numerical matrix in R computational environment. In our case we have downsized it to 8 × 8 to present it in all clarity and show the relevance of different processing algorithms and visualization. This transformed Covid positive chest radiograph as a 8 × 8 matrix is displayed in Fig. 2 and different color intensities show different grey levels in original covid positive chest radiograph.

Fig. 1 Chest X-Ray

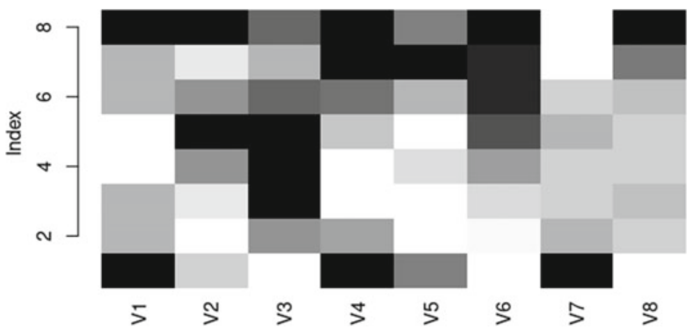

Fig. 2 Matrix Representation

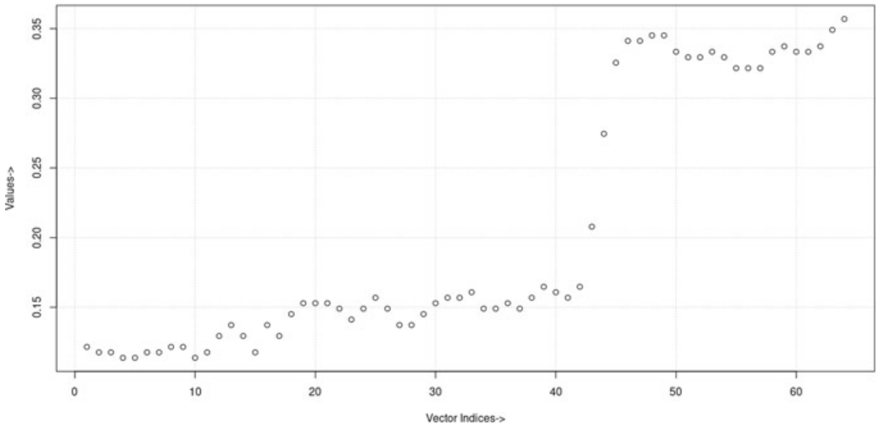

Fig. 3 Matrix to vector conversion of COVID positive training image, COVID_Train7 and corresponding plot of values

In next stage of transformation this 8 × 8 matrix is stacked as a vector of size 64 and is plotted as a time series in Fig. 3. Now stage is set for the transformation of this timeseries to a horizontal visibility graph. Once horizontal visibility graph algorithm processes this timeseries, a network is generated whose adjacency plot is shown in Fig. 4. Its largely sparse graph with few connectivity here and there as displayed by yellow-colored cells. Real network shape and connectivity patterns of horizontal visibility graph is demonstrated in Fig. 5. It can be visualized in multiple ways in R environment and exposes larger number of features and properties of horizontal visibility graphs resulting from chest radiographs.

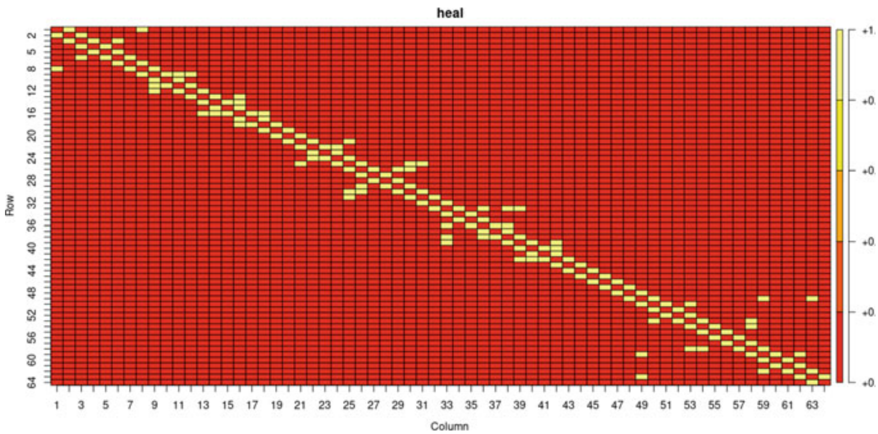

Fig. 4 Adjacency matrix plot of horizontal visibility graph generated from COVID positive training image, COVID_Train7.jpeg. Only yellow cells are one indicating connectivity and rest are disconnected

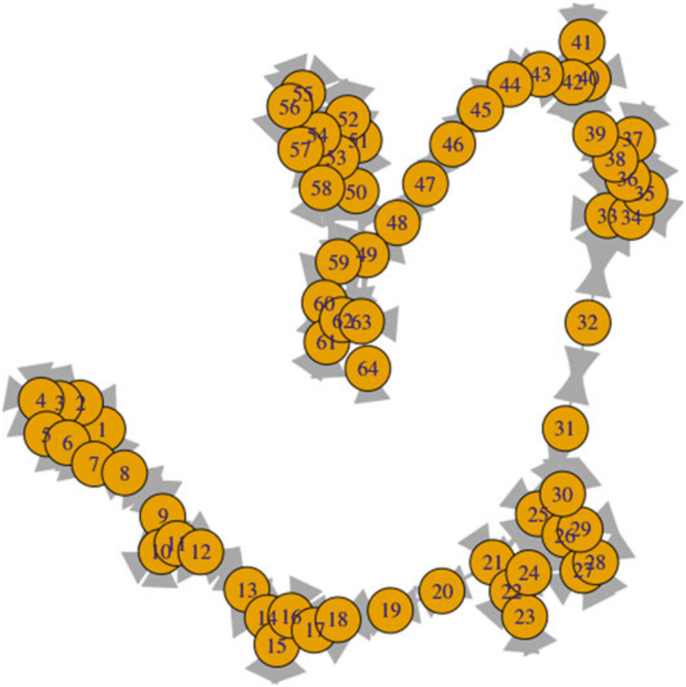

Fig. 5 Network plot of horizontal visibility graph generated from COVID positive training image, COVID_Train7

Before we move to next Fig. 6, we need to recollect the definition of heatmap. A heatmap is a two-dimensional grid kind of visual representation of data/information/signal in a colorful fashion. Heatmaps can aide the viewer in trying to make sense of a complex spatial distribution of information. What Fig. 6 shows is connectivity activity on a two-dimensional grid to communicate in a user-friendly fashion. Figure 7 provides another view of same horizontal visibility graph obtained from Covid positive image and Fig. 8 shows the same diagram with node size being proportional to 5th power of the degree of the node, i.e. highly connected nodes or hubs are depicted with larger circles as compared to sparsely connected nodes. Figures 9 and 10 show the degree distribution and cumulative degree.

A histogram type horizontal visibility graph is demonstrated in Fig. 11 obtained from Covid positive chest radiograph data. Its curvy form is demonstrated in Fig. 12. Both demonstrate interesting connectivity patterns. At this stage Covid positive chest radiograph's HVG is ready to be used by HIM-distance metric to compute similairty among different HVGs generated from normal and Covid positive chest radiographs.

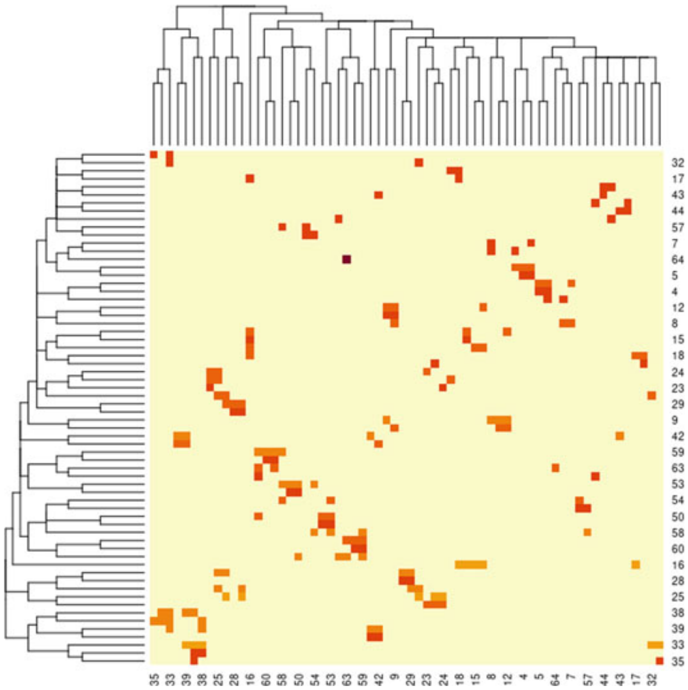

Fig. 6 Heatmap of horizontal visibility graph generated from COVID positive training image, COVID_Train7

4.2 Computational Infrastructure Deployed

Matlab has been used for performing geometrical part of the work. EMD aspect of this work has been performed in R software (Rstudio Version 1.3.1093 ©2009–2020 RStudio, PBC"Apricot Nasturtium" (aee44535, 2020-09-17) for Ubuntu Bionic Mozilla/5.0 (X11; Linux x86i 64) AppleWebKit/537.36 (KHTML, like Gecko) QtWebEngine/5.12.8 Chrome/69.0.3497.128 Safari/537.36) on a HP Probook laptop.

Laptop's operating system and other basic information from comand uname -a is given below:

Linux Krishna 5.4.0–48-generic #52-Ubuntu SMP Thu Sep 10 10:58:49 UTC 2020

$\times$ 86 64 $\times$ 86i 64 $\times$ 86 64 GNU/Linux

Output of hardware atributes of the laptop is as follows:

-memory

description: System memory

physical id: 0

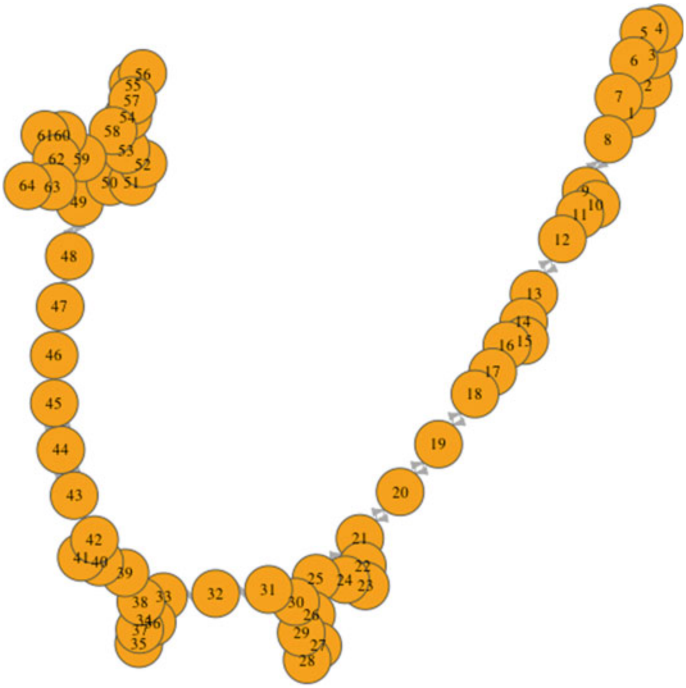

Fig. 7 Another network view of horizontal visibility graph generated from COVID positive training image, COVID_Train7

size: 8320MiB

-cpu

product: Intel(R) Core(TM) i5-8250U CPU @ 1.60 GHz

vendor: Intel Corp.

physical id: 1

bus info: cpu@0

size: 3304 MHz

capacity: 3400 MHz

Finally, Fig. 13 depicts the flow chart for Covid computational disease tagging algorithm using Visibility graph and network distance HIM in a sequential fashion. It summarizes all the computational steps used in different stages of processing at high level.

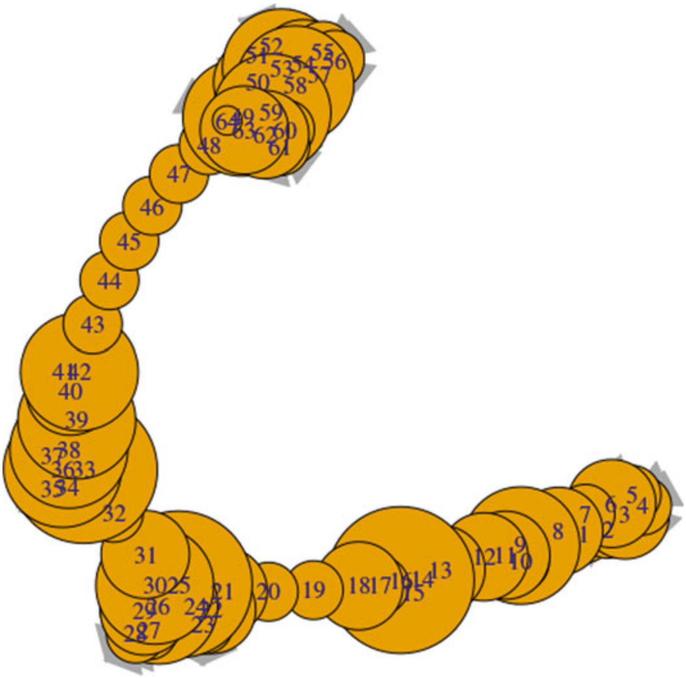

Fig. 8 Network view with node size 5th power of degree for horizontal visibility graph generated from COVID positive training image, COVID_Train7.jpeg

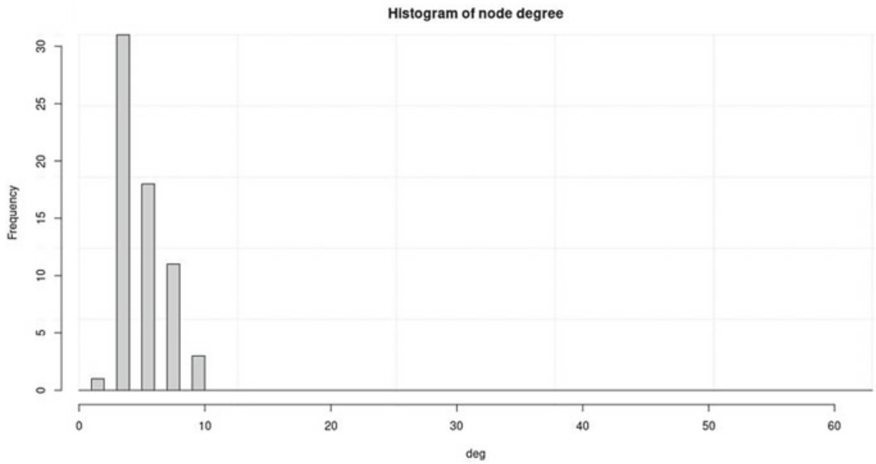

Fig. 9 Histogram of degree for horizontal visibility graph generated from COVID positive training chest radiograph, COVID Train7.jpeg. Moderately connected

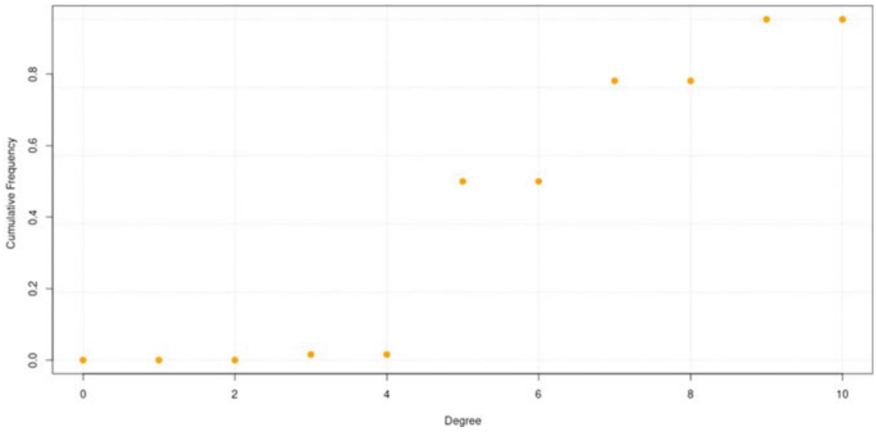

Fig. 10 Cumulative degree distribution for horizontal visibility graph generated from COVID positive training chest radiograph, COVID Train7.jpeg. Moderately connected

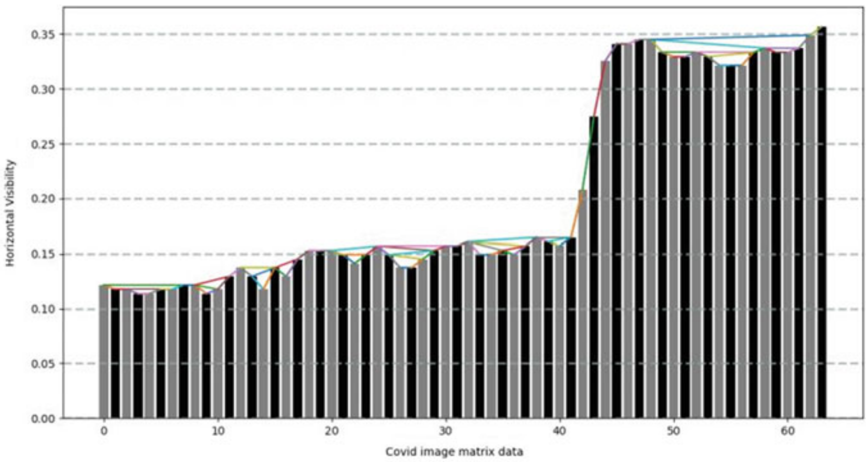

Fig. 11 Covid image matrix data

5 Experimental Results

5.1 Computational Experiment

This part describes the result of automated disease tagging using horizontal visibility graph and HIM based network similarity (distance) computation. Chest radiographs used here are sourced from Rajiv Gandhi Cancer Institute and Research Centre [64, 63].

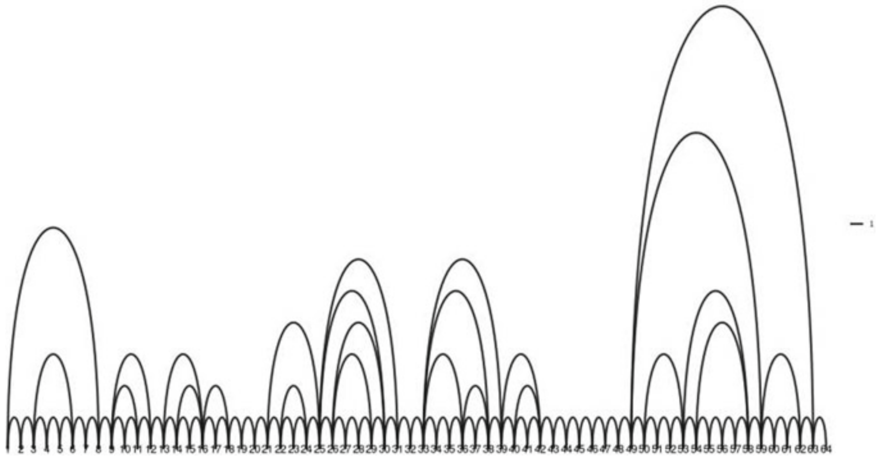

Fig. 12 Visibility graph generated from COVID positive training chest radiograph, COVID Train7.jpeg

Data Preprocessing To keep the computation of images and their processing commensurate to hardware platform capabilities, all the radiographs acquired are converted into the JPG format. For fast processing and declaration of results in almost-real-time, radiographs are down sampled to the 32×32 pixel size irrespective of their original size.

Radiograph data is grouped into two main groups, training and testing. Training group has 10 normal and 10 covid positive radiographs. Normal radiographs are compared amongst each other using HVG–HIM algorithm and representative normal radiograph is computed like our previous work using EMD as shown in Table 1. Same process is followed for the covid positive radiograph and a covid-positive representative radiograph is obtained. Out of multiple network distance available, Hamming-Ipsen Mikhailov (HIM) network distance is used for comparing the visibility graphs because of its balanced nature as a both global and local network distance or similarity metric.

Training Using Normal Chest Radiographs As shown in the flowchart in Fig. 13, we begin with evaluating the normal representative chest radiograph (Normal-Rep) among normal ensemble of training chest radiographs. This Normal-Rep will be used to compare the test chest radiograph with, to decide if test chest radiograph can be tagged normal or Covid-positive. This process of computing Normal-Rep is by converting all the normal training chest radiographs into visibility graphs and measuring their computational similarity with HIM metric. The Table 1 for deciding Normal-Rep is given below where third normal training chest radiograph has been designated Normal-Rep for this ensemble of ten normal training chest radiographs due to its highest similarity (Hence lowest column sum score) with all other normal training chest radiographs. Its score is indicated in third column and sum row in bold.

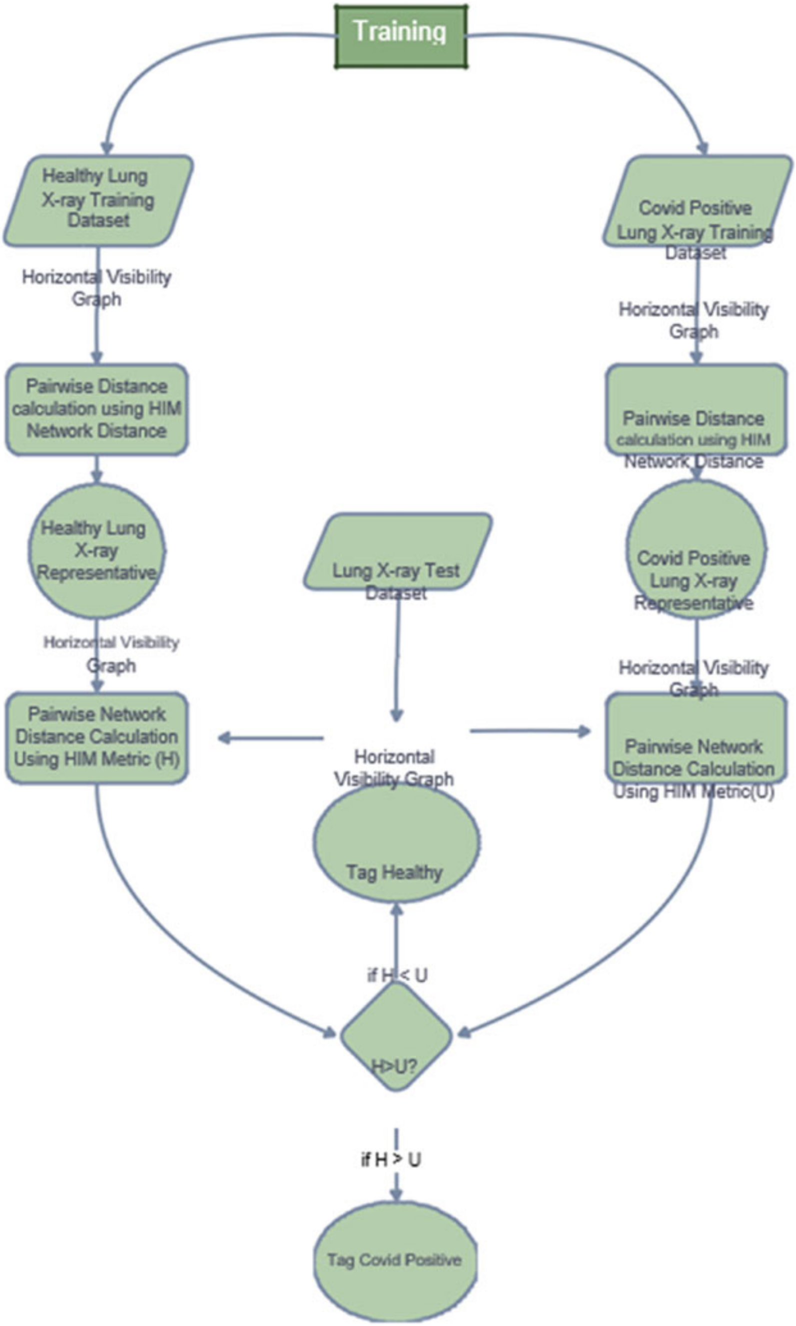

Fig. 13 Flow chart for Covid computational disease tagging algorithm using Visibility graph and Network Distance HIM

Table 1 HIM score table for computing HIM distance among normal chest radio-graphs and locating normal-Rep

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
1	0	0.002114	0.002061	0.002169	0.001873	0.002119	0.001924	0.001924	0.002170	0.001863
2	0.002114	0	0.001683	0.002144	0.002102	0.002152	0.002041	0.002028	0.002145	0.002044
3	0.002061	0.001683	0	0.002087	0.002007	0.001991	0.001995	0.001921	0.001966	0.002038
4	0.002169	0.002144	0.002087	0	0.002027	0.001768	0.002079	0.002110	0.002246	0.002099
5	0.001873	0.002102	0.002007	0.002027	0	0.002071	0.001885	0.001963	0.002217	0.001893
6	0.002119	0.002152	0.001991	0.001768	0.002071	0	0.002091	0.002117	0.002258	0.002079
7	0.001924	0.002041	0.001995	0.002079	0.001885	0.002091	0	0.001881	0.002090	0.001935
8	0.001924	0.002028	0.001921	0.002110	0.001963	0.002117	0.001881	0	0.002115	0.001783
9	0.002170	0.002145	0.001966	0.002246	0.002217	0.002258	0.002090	0.002115	0	0.002147
10	0.001863	0.002044	0.002038	0.002099	0.001893	0.002079	0.001935	0.001783	0.002147	0
Sum	0.018220	0.018457	0.017754	0.018733	0.018043	0.018649	0.017924	0.017846	0.019357	0.017886

Training Using Covid Positive Chest Radiographs Following the flowchart in Fig. 1. We begin with evaluating the Covid Positive representative chest radiograph (Covid-PositveRep) among Covid positive ensemble of training chest radiographs. This Covid Positive-Rep will be used to compare the test chest radiograph with, to decide if test chest radiograph can be tagged normal or Covid-positive. This process of computing CovidPositiveRep is realized by converting all the Covid Positive training chest radiographs into visibility graphs and measuring their computational similarity with HIM metric. The Table 2 for deciding Covid Positive-Rep is given below where fourth Covid positive training chest radiograph has been designated Covid Positive-Rep for this ensemble of ten Covid positive training chest radiographs due to its highest similarity (Hence lowest column sum score) with all other Covid positive training chest radiographs. Its score is indicated in fourth column and sum row in bold.

Final Testing and Automated Disease Tagging for Test Chest Radiographs Using HVG–HIM In, the follow-up testing phase, both healthy and covid positive representative radiographs are compared using HIM distance with pretagged test dataset of 20 radiographs. This test dataset has both healthy and covid positive radiographs. The result of automated disease tagging is presented below. Let's define U as HIM Distance from Covid Positive representative and H as HIM Distance from Healthy representative. A simple observation tells us that this algorithm is able to tag the chest radiographs with overall accuracy of 60%. Healthy radiographs have been tagged with 60% accuracy and also covid positive radiographs are tagged with 60% accuracy. A natural future direction arises where other network distance metrics can be leveraged over larger datasets (Fig. 12, Table 3).

6 Final Testing and Automated Disease Tagging for Test Chest Radiographs with EMD

To draw a fair comparison between EMD and HVZ-VG, we run the same computational with direct perceptual similarity between chest radiographs-based evaluation and diseases tagging with EMD. To keep the computation of chest radiographs and their processing commensurate to hardware platform capabilities, all the radiographs acquired are converted into the JPG format. For fast processing and declaration of results in almost-real-time, radiographs are down sampled to the 32×32-pixel size irrespective of their original size. This is in consonance with the same computational experiment carried out HVG–HIM. Results of EMD-based disease tagging is shown in Table 4 where a meagre 30% accuracy is reported, and correct disease tag rows are highlighted in bold. This is in sharp contrast with accuracy of 60% achieved with HVZ–HIM, albeit at a higher computational investment.

Table 2 HIM score table for computing HIM distance among covid positive chest radiographs and locating covid positive-Rep

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
1	0	0.001879	0.001896	0.001809	0.001768	0.001861	0.001897	0.001996	0.001989	0.002110
2	0.001879	0	0.001882	0.001690	0.001873	0.001820	0.001738	0.001784	0.001838	0.001814
3	0.001896	0.001882	0	0.001825	0.001755	0.001837	0.001948	0.001865	0.001738	0.001981
4	0.001809	0.001690	0.001825	0	0.001880	0.001991	0.001619	0.001845	0.001640	0.001760
5	0.001768	0.001873	0.001755	0.001880	0	0.001728	0.002055	0.002103	0.001936	0.002020
6	0.001861	0.001820	0.001837	0.001991	0.001728	0	0.001773	0.001903	0.002042	0.001873
7	0.001897	0.001738	0.001948	0.001619	0.002055	0.001773	0	0.001780	0.001783	0.001598
8	0.001996	0.001784	0.001865	0.001845	0.002103	0.001903	0.001780	0	0.001767	0.001875
9	0.001989	0.001838	0.001738	0.001640	0.001936	0.002042	0.001783	0.001767	0	0.001881
10	0.002110	0.001814	0.001981	0.001760	0.002020	0.001873	0.001598	0.0018758	0.001881	0
Sum	0.017209	0.016324	0.016731	0.016063	0.017122	0.016833	0.016195	0.016921	0.016618	0.016916

Table 3 HIM score based disease tagging table for test covid positive and normal chest radiographs using HVG–HIM

No	U	H	Real Tag	VG-HIM Tag
1	0.001738350	0.002092146092198	Covid positive	Covid positive
2	0.002082185	0.001840777512553	Covid positive	Normal
3	0.001950630	0.00211087540523	Covid positive	Covid positive
4	0.001840535	0.001930288747592	Covid positive	Covid positive
5	0.002241159	0.001995573933206	Covid positive	Normal
6	0.001916763	0.001973678120048	Covid positive	Covid positive
7	0.001955399	0.002161508372919	Covid positive	Covid positive
8	0.001919654	0.001948495673396	Covid positive	Covid positive
9	0.002331740	0.002206820660675	Covid positive	Normal
10	0.002041363	0.00186923269593	Covid positive	Normal
11	0.001997673	0.001997358118727	Normal	Normal
12	0.002224062	0.002132561182092	Normal	Normal
13	0.001828268	0.001921438899592	Normal	Covid positive
14	0.002111531	0	Normal	Normal
15	0.002106018	0.002075943450341	Normal	Normal
16	0.001789069	0.002062848422154	Normal	Covid positive
17	0.002076307	0.002162210255525	Normal	Covid positive
18	0.002154178	0.001964655126736	Normal	Normal
19	0.001989834	0.002014787858529	Normal	Covid positive
20	0.002301401	0.002209421305833	Normal	Normal

7 Reflections on HVG–HIM and EMD Similarity Metrics

This experiment on working with HVG–HIM and EMD has given us certain insights into the implementation of these algorithms. Earth Movers Distance (EMD) algorithm computes the discrepancy pixel by pixel in the chest radiographs and gives us the overall average difference between the chest radiographs as a similarity metric. In the case of horizontal visibility graph (HVZ), each pixel compares itself with all other pixels of the same chest radiograph and gives a graphical representation. This graphical representation of one chest radiograph is compared with other chest radiographs's graphical representation using the network distance metric. For calculating the difference in these graphs various network distance metrics can be used. Here, we have used HammingIpsen-Mikhailov (HIM) distance.

From a computational aspect, EMD does far fewer calculations than HVG–HIM metric does. EMD computes the results within the few seconds for given set of ten chest radiographs with similar size whereas for the same task HVG–HIM network

Table 4 EMD score based disease tagging table for test covid positive and normal chest radiographs

No	EMD from NormalRep	EMD from CovidPositive-Rep	Real-Tag	EMD-Tag
1	0.50817084312439	0.102157711982727	Normal	CovidPositive
2	3.02615809440613	0.244212314486504	Normal	CovidPositive
3	0.554616451263428	0.10110604763031	Normal	CovidPositive
4	2.75559902191162	1.02294194698334	Normal	CovidPositive
5	1.33040499687195	0.4100721180439	Normal	CovidPositive
6	0.52178567647934	0.358028054237366	Normal	CovidPositive
7	1.14510023593903	4.19615602493286	Normal	Normal
8	0.391091376543045	0.514602303504944	Normal	Normal
9	1.55246329307556	0.12182080745697	Normal	CovidPositive
10	0.939411997795105	0.931683301925659	Normal	CovidPositive
11	1.28701484203339	0.468866437673569	CovidPositive	CovidPositive
12	1.32051146030426	1.4063401222229	CovidPositive	Normal
13	1.10182595252991	3.01665210723877	CovidPositive	Normal
14	0.449742645025253	1.7027291059494	‘ CovidPositive	Normal
15	0.765507996082306	1.09815609455109	CovidPositive	Normal
16	0.297308087348938	0.422655075788498	CovidPositive	Normal
17	‘0.361823529005051	0.790895044803619	CovidPositive	Normal
18	0.480859369039536	0.396273583173752	CovidPositive	CovidPositive
19	0.886679291725159	0.466326594352722	CovidPositive	CovidPositive
20	1.08181118965149	0.41103208065033	CovidPositive	CovidPositive

distance takes several minutes. Clearly, there is a learning that details matter. HVG–HIM is giving twice the accuracy of 60% compared to EMD which gives the accuracy of 30% for the same task. Naturally, HVG–HIM is achieving this performance because of large computational investment. This leads to an interesting deployment choice as in, where chances of Covid-positive prevalence is extremely low and high accuracy is not needed, one can deploy EMD based procedures but for regions where prevalence is higher and accuracy is of paramount importance, HVZ-HIM with serious computational infrastructure will be needed.

8 Towards a Web-Service Based Implementation

Covid has emerged as an unprecedented global pandemic with serious impact on every individual. Provision of immediate and adequate health infrastructure for covid patients visiting a health service facility or practicing tele consultancy based on pathological examination of chest radiograph is the need of the hour. After centuries of advancements and developments in different health practices like Allopathy, Ayurved, Homeopathy and other forms of treatment strategies, human efforts against Covid has been dwarfed. The whole medical community is fighting with all available resources to tackle the situation and treat the patients. Having said that it is hard to deny in comparison to covid patients, the number of skilled and trained health workers like doctors, nurses and other health service providers is not sufficient, owing to this provisioning gap, high mortality and prolonged morbidity is recorded, especially in LMICs (Low- and Middle-income Countries.)

Today, we are living in a digital world where enormous amount of technology enabled health services are being practiced all across the world specially in the form of digital health encompassing—tele consultancy, telemedicine, telehealth, big data etc. They help in gathering meaningful information, processing it and producing the report in almost real-time so that the policy makers can formulate evidence-based health strategies leading to follow-up of patients more effectively.

Keeping this urgent need in mind, we have developed our own web-portal which is capable of collaborating with all the hospitals and individual medical practioners/patients through a centralized server. This server is designed in such a manner that any individual or hospital can access the server after proper validation and store their relevant information related to patients. Data security and confidentiality has been maintained by the server strictly. Edit access has been limited to information owners only on the portal. The purpose of this webservice is to store the information, process it and produce the result in form of scientific evidence which can be significantly utilized by policy makers for better decision making. At the same time, by accessing the portal, one can get all the relevant and accurate information related to Covid in form of text, presentation and multimedia (audio/video/images). This portal will also provide an individual specific service like tele consultancy to register and forward the unanswered queries directly to the specialist doctors and back to the query generator (possibly patient or someone curious about a medical condition) (Figs. 14 and 15).

8.1 Webservice Methodology

The web-based healthcare management system for Covid patients is poised with the latest front and web-page development language—PhP 7.3.28 and the core technology used is MVC (Model View Controller). There are different modules in the website which incorporate API (Application Programming Interface) to interact with dedicated servers for dedicated processing of HVG and HIM-distance in terms of image analysis using R (RStudio 3.6.3) and other statistical packages and report generation with an attractive and effective graphical representation for the available dataset. MySQL server is used as the backend RDBMS (Relational database Management System) for data input, process, and output to APIs and individuals for usage downstream. We have integrated these technologies because they are opensource and compatible for design, development, and deployment. Further, they are

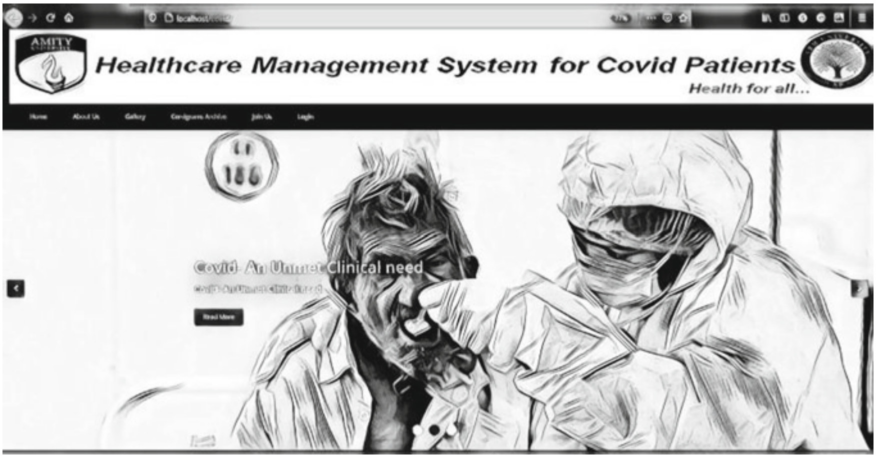

Fig. 14 Transiton from research to service provision: A pilot webservice for automated COVID disease tagging

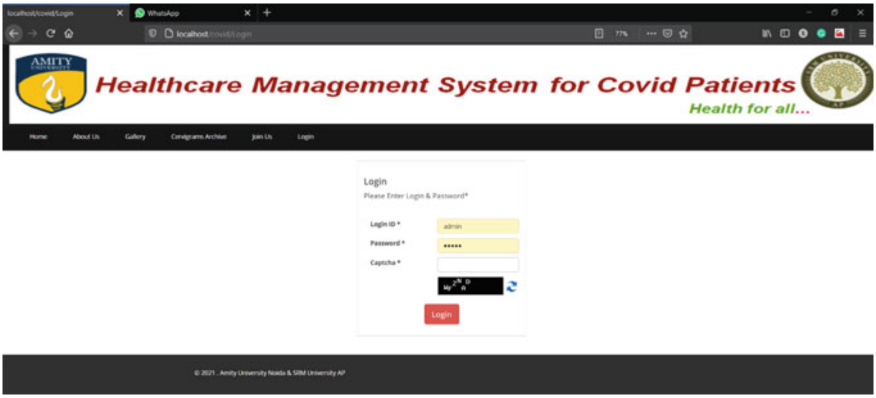

Fig. 15 Resource for Automated disease tagging with chest radiographs in LMICs and resource challenged African Countries

customizable as per the medical data-keeping requirements of this project. Security and confidentiality are maintained at all levels of data flow starting from information gathering to report generation. A brief architecture of webservice technology has been shown in Fig. 16.

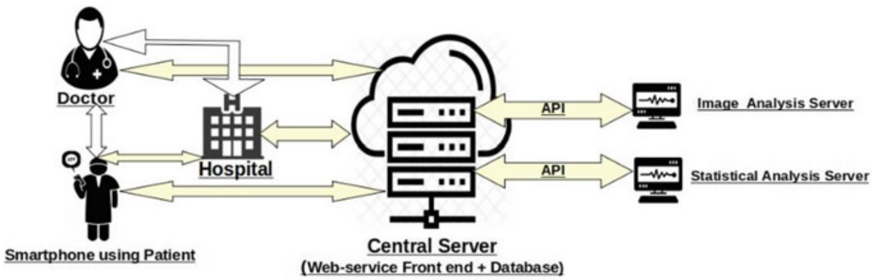

Fig. 16 Web Service Architecture for Covid Positive Chest Radiograph based Disease Tagging

9 Conclusions and Future Directions

Poor lung health is known to play a statutory role causing increased susceptibility related to COVID-19. Lifestyle choices including smoking and sedentary lifestyle leading to obesity aren't the only factors that influences lung health, environmental factors such as air pollution also exert a considerable effect. Researchers believe that while consumption of tobacco products (both smoking and smokeless), along with occupational hazards such as exposure to indoor and outdoor pollution makes people more susceptible to the infection that causes COVID-19 and its complications because these environmental factors also significantly damage the body's natural defenses against some bacteria and viruses. A large number of countries coming under the umbrella of LLMICs having populations endowed with poor lung function and consequently poor lung health reflect their health outcomes as poor.

The use of extant deep learning technologies is not necessarily solving the problem of integrating the evidences from the community level in resource limited healthcare systems as they are intensive and energy-hogging with respect to computational resources leading to increased carbon foot-printing and hence global warming.

To this end use of static algorithms such as Earth Movers Distance (EMD) and Horizontal Visibility Graph (HVG) add value as they require significantly lesser investment of computational resources and dispel the black box nature of the deep learning algorithms with the glass box nature with more transparency with respect to big data computation and analytics [65]. We propose to extend our studies on the use of EMD and HVG based time series analysis, in which dynamic timeseries and clinical multimedia segments are mapped to visibility graphs as being descriptions of the corresponding states and the successively occurring states are linked. This procedure capable of converting a dynamic time series to a temporal network and at the same time a network of networks could be provide us rich information benefiting short-term and long-term predictions about lung of an individual or community at large, thereby providing the policy administrators at local, regional and global level nuanced data for developing comprehensive niche specific solutions aimed at alleviating the lung-health disparities.

Use of multi-modal multi sensor fusion technologies combined with big data enabled platforms will go a long way in strengthening resource-deprived healthcare systems. Our proposed disruptive AI-enabled point of care solution aims to gather evidences from the community level so as to augment catering to the creation of affordable and accessible healthcare technologies will focus on the application of innovative concepts to improve health outcomes in an affordable and equitable manner to overcome healthcare disparities but also inculcate capacity building through the provision of unique platform to individuals /organizations to validate their proof of concepts to scale-ups and ultimately commercially viable sustainable solutions.

10 Device Utility

1. Has potential application as an Adjunct Clinical Aid for the Pulmonologist/Medical Professionals.
2. Automatic Classification of X-ray chest radiographs facilitating large scale screening of subjects in remote health camps.
3. Easy, fast and robust technology with capabilities to be implemented in web-based, desktop-based and smartphone-based applications when coupled with X-ray device on the internet.
4. It has potential of turning Covid disease management as a self-care exercise. Control moves from the hands of expensive hospital to cheap and affordable selfcare devices.

References

1. United Nations: Report of the director-general of the World Health Organization on the prevention and control of non-communicable diseases. Document A/R68/650 (2013). Accessed 15 Nov 2020
2. Dutta, U., Nagi, B., Garg, P.K., Sinha, S.K., Singh, K., Tandon, R.K.: Patients with gallstones develop gallbladder cancer at an earlier age. Eur. J. Cancer Prev. **14**, 381–385 (2005). https://doi.org/10.1097/00008469-200508000-00011
3. Gajalakshmi, C.K., Shanta, V., Swaminathan, R., Sankaranarayanan, R., Black, R.J.: Apopulation-based survival study on female breast cancer in Madras. Br. J. Cancer Res. **75**, 771–5 (1997). https://doi.org/10.1038/bjc.1997.137
4. Mendis, S.: Global status report on noncommunicable diseases 2014 (2014). http://www.who.int/nmh/publications/ncd-status-report-2014/en/. Accessed 15 Nov 2020
5. United Nations: Outcome document of the high-level meeting of the General Assembly on the comprehensive review and assessment of the progress achieved in the prevention and control of non-communicable diseases. A/RES/68/300 (2014). Accessed 15 Nov 2020
6. World Health Organization. Novel coronavirus—China. http://www.who.int/csr/zxcvXDdon/12-january-2020-novel-coronavirus-china/en/. Accessed: 15 Nov 2020

7. World Health Organization. Naming the coronavirus disease (COVID-19) and the virus that causes it. https://www.who.int/emergencies/diseases/novelcorona-virus2019/technical-guidance/naming-the-coronavirus-disease-(COVID-2019)-andthe- virus-that-causes-it. Accessed 15 Nov 2020
8. Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., et al.: Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet **395**, 497–506 (2020)
9. World health organization (WHO): COVID 19 and NCDs. https://www.who.int/emergencies/diseases/novel-coronavirus-2019. Accessed 15 Nov 2020
10. Leung, C.: Clinical features of deaths in the novel coronavirus epidemic in China. Rev. Med. Virol. **30**(3), e2103 (2020)
11. Chen, N., Zhou, M., Dong, X., Qu, J., Gong, F., Han, Y., et al.: Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. Lancet **395**, 507–513 (2020)
12. GBD: Chronic Respiratory Disease Collaborators. Global, regional, and national deaths, prevalence, disability-adjusted life years, and years lived with disability for chronic obstructive pulmonary disease and asthma, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. Lancet Respir. Med. **5**, 691–706 (2017)
13. India State-Level Disease Burden Initiative CRD Collaborators: The burden of chronic respiratory diseases and their heterogeneity across the states of India: The Global Burden of Disease Study 1990–2016. Lancet Global Health **6**(12), e1363–e1374 (2018). https://doi.org/10.1016/S2214-109X(18)30409-1.28N.Chavanetal
14. Cohen, A.J., Brauer, M., Burnett, R., et al.: Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. Lancet **389**, 1907–1918 (2017)
15. Landrigan, P.J., Fuller, R., Acosta, N.J.R., et al.: The lancet commission on pollution and health. Lancet **391**, 462–512 (2018)
16. Rubner, Y., Tomasi, C.: The earth movers distance perceptual metrics for image database navigation. (2001)
17. Ji, H., Xu, T., Wu, W., Wang, J.: Visibility graph analysis on EEG signal. In: 2016 9th International Congress on Image and Signal Processing, pp. 1557–1561. BioMedical Engineering and Informatics (CISP-BMEI), Datong (2016). https://doi.org/10.1109/CISP-BMEI.2016.7852963
18. Thompson, N.C., Greenewald, K., Lee, K., Manso, G.F.: The Computational Limits of Deep Learning (2020). arxiv:2007.05558
19. Yampolskiy, R.V.: Unpredictability of AI (2019). Arxiv:1905.13053
20. Yampolskiy, R.V.: Unexplainability and incomprehensibility of artificial intelligence (2019). Arxiv:1907.03869
21. Sohl-Dickstein, J., Weiss, E.A., Maheswaranathan, N., Ganguli, S.: Deep unsupervised learning using nonequilibrium thermodynamics (2018). Arxiv:1503.03585
22. Li, H.: Analysis on the nonlinear dynamics of deep neural networks: topological entropy and chaos (2018). Arxiv:1804.03987
23. Shrivastav, K.D., Taneja, N., Das, A.M., Rana, S., Ranjan, P., Singh, H., Jaggi, V.K., Janardhanan, R.: Socio-demographic and clinico-pathological profile of cervical cancer patients at a tertiary care centre in New Delhi: a five-year retrospective analysis. Indian J. Community Health **33**(4) (2021)
24. Shrivastav, K.D., Arambam, P., Batra, S., Bhatia, V., Singh, H., Jaggi, V.K., Ranjan, P., Abed, E.H., Janardhanan, R.: Earth mover's distance-based tool for rapid screening of cervical cancer using cervigrams. Appl Sci **12**(9), 4661 (2022)
25. https://venturebeat.com/2020/07/15/mit-researchers-warn-that-deep-learning-isapproaching computational-limits. Published 15 July 2020
26. Scassellati, C., Bonvicini, C., Benussi, L., Ghidoni, R., Squitti, R.: Neurodevelopmental disorders: Metallomics studies for the identification of potential biomarkers associated to diagnosis and treatment. J. Trace Elem.Ts Med. Biol. **60**, 126499 (2020). https://doi.org/10.1016/j.jtemb.2020.126499. ISSN 0946-672X

27. Chen, R.J., Lu, M.Y., Wang, J., Williamson, D.F.K., Rodig, S.J., Lindeman, N.I., Mahmood, F.: Pathomic Fusion: An Integrated Framework for Fusing Histopathology and Genomic Features for Cancer Diagnosis and Prognosis (2019). https://arxiv.org/abs/1912.08937
28. Carmichael, I., Calhoun, B.C., Hoadley, K.A., Troester, M.A., Geradts, J., Couture, H.D., Olsson, L., Perou, C.M., Niethammer, M., Hannig, J., Marron, J.S.: Joint and individual analysis of breast cancer histologic images and genomic covariates (2019). https://arxiv.org/abs/1912.00434
29. Carmichael, I., Calhoun, B.C., Hoadley, K.A., Troester, M.A., Geradts, J., Heather, D.C., Olsson, L., Perou, C.M., Niethammer, M., Hannig, J., Marron, J.S.: Joint and individual analysis of breast cancer histologic images and genomic covariates (2019). https://arxiv.org/abs/1912.00434
30. Guo, A., Chen, Z., Li, F., Li, W., Luo, Q.: Towards more reliable unsupervised tissue segmentation via integrating mass spectrometry imaging and hematoxylin-erosin stained histopathological image (2020). https://www.biorxiv.org/content/https://doi.org/10.1101/2020.07.17.208025v1
31. Ozturk, T., Talo, M., Yildirim, E.A., Baloglu, U.B., Yildirim, O., Acharya, U.: Automated detection of COVID-19 cases using deep neural networks with. Comput. Biol. Med. **1**, 11 (2020)
32. Guo, A., Chen, Z., Li, F., Li, W., Luo, Q.: Towards more reliable unsupervised tissue segmentation via integrating mass spectrometry imaging and hematoxylin-erosin stained histopathological image (2020). https://www.biorxiv.org/content/https://doi.org/10.1101/2020.07.17.208025v1
33. Lacasa, L., Luque, B., Ballesteros, F., Luque, J., Nuno, J.C.: From time series to complex networks: the visibility graph. In: Proceedings of the National Academy of Sciences, vol. 105, 13th edn, pp. 4972–4975 (2008)
34. Luque, B., Lacasa, L., Ballesteros, F., Luque, J.: Horizontal visibility graphs: exact results for random time series. Phys. Rev. E **80**(4), 046103 (2009)
35. Zhu, G., Li, Y., Wen, P.: Analysis and classification of sleep stages based on difference visibility graphs from a single-channel EEG signal. IEEE J. Biomed. Health Inform. **18**(6), 1813–1821 (2014)
36. Donner, R.V., Donges, J.F.: Visibility graph analysis of geophysical time series: potentials and possible pitfalls. Acta Geophys. **60**(3), 589–623 (2012)
37. Sannino, S., Stramaglia, S., Lacasa, L., Marinazzo, D.: Visibility graphs for fMRI data: Multiplex temporal graphs and their modulations across resting-state networks. Netw. Neurosci. **1**(3), 208–221 (2017)
38. Iacovacci, J., Lacasa, L.: Visibility graphs for image processing. IEEE Trans. Pattern Anal. Mach. Intell. **42**(4), 974–987 (2019)
39. Madl, T.: Network analysis of heart beat intervals using horizontal visibility graphs. In: 2016 Computing in Cardiology Conference (CinC), pp. 733–736. IEEE (2016)
40. Artameeyanant, P., Sultornsanee, S., Chamnongthai, K.: An EMG-based feature extraction method using a normalized weight vertical visibility algorithm for myopathy and neuropathy detection. Springerplus **5**(1), 1–26 (2016)
41. Fasmer, E.E., Fasmer, O.B., Berle, J.Ø., Oedegaard, K.J., Hauge, E.R.: Graph theory applied to the analysis of motor activity in patients with schizophrenia and depression. PloS one **13**(4), e0194791 (2018)
42. Mohammadpoory, Z., Nasrolahzadeh, M., Mahmoodian, N., Sayyah, M., Haddadnia, J.: Complex network based models of ECoG signals for detection of induced epileptic seizures in rats. Cogn. Neurodyn. **13**(4), 325–339 (2019)
43. Flanagan, R., Lacasa, L., Nicosia, V.: On the spectral properties of Feigenbaum graphs. J. Phys. A: Math. Theor. **53**(2), 025702 (2019)
44. https://onezero.medium.com/training-a-neural-network-can-emit-more-than-600-000-pounds-of-co2-but-not-for-long-d3074c1383fd
45. https://www.nature.com/articles/d41586-019-03013-5

46. Ranjan, P., Shrivastav, K.D., Vadlamani, S., Janardhanan, R.: HRIDAI:A tale of two categories of ECGs. In: International Symposium on Signal Processing and Intelligent Recognition Systems, pp. 243–263. Springer, Singapore (2020)
47. Kermali, M., Khalsa, R.K., Pillai, K., Ismail, Z., Harky, A.: The role of biomarkers in diagnosis of COVID-19—a systematic review. Life Sci. **254**: 117788 (2020). https://doi.org/10.1016/j.lfs.2020.117788. Epub 2020 May 13. PMID: 32475810; PMCID: PMC7219356
48. Leulseged, T.W., Hassen, I.S., Ayele, B.T., Tsegay, Y.G., Abebe, D.S., Edo, M.G., Maru, E.H. et al.: Laboratory biomarkers of COVID-19 disease severity and outcome: Findings from a developing country. Plos one **16**(3), e0246087 (2021)
49. Shrivastav, K.D., Arambam, P., Das, A.M., Saeed, S., Kaul, U., Ranjan, P., Janardhanan, R.: Earth mover's distance-based automated geometric visualization/classification of electrocardiogram signals. Trends Commun. Cloud Big Data 75–85 (2020)
50. Taneja, A., Ujlayan, A., Janardhanan, R., Ranjan, P.: Pancreatic cancer detection by an integrated level set-based deep learning model. Big Data Artif. Intell. Healthc. Appl. (2021). https://doi.org/10.1201/9781003093770-8
51. Khatri, A., Jain, R., Vashista, H., Mittal, N., Ranjan, P., Janardhanan, R.: Pneumonia identification in chest X-ray images using EMD. Trends Commun. Cloud Big Data 87–98 (2020). 9780367698393 C008.indd 180 14/06/21 11:24 PM
52. Goyal, A., Tirumalasetty, S., Bathla, D., Arya, M.K., Agrawal, R., Ranjan, P., Hossain, G., Challoo, R.: A computational segmentation tool for processing patient brain MRI image data to automatically extract gray and white matter regions. In: Emerging Research in Computing, Information, Communication and Applications, pp. 1–16. Springer, Singapore (2019)
53. Shrivastav, K.D., Das, A.K., Singh, H., Ranjan, P., Janardhanan, R.: Classification of colposcopic cervigrams using EMD in R. In: International Symposium on Signal Processing and Intelligent Recognition Systems, pp. 298–308. Springer, Singapore, 2018
54. Taneja, A., Ranjan, P., Ujlayan, A.: Multi-cell nuclei segmentation in cervical cancer images by integrated feature vectors. Multimed. Tools Appl. **77**(8), 9271–9290 (2018)
55. Taneja, A., Ranjan, P., Ujlayan, A.: An efficient SOM and EM-based intravascular ultrasound blood vessel image segmentation approach. Int. J. Syst. Assur. Eng. Manag. **7**(4), 442–449 (2016)
56. Taneja, A., Ranjan, P., Ujlayan, A.: Novel texture pattern based multi-level set segmentation in cervical cancer image analysis. In: Proceedings of the International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV), p. 76. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp) (2016)
57. Agarwal, A., Ali, F., Kopparthi, A., Shrivastava, K.D., Ranjan, P., Jananardhanan, R.: Specular reflection removal in cervigrams. In: Proc. of CCB. Springer-Nature (2020)
58. Chavan, N., Ranjan, P., Kumar, U., Shrivastav, K.D., Janardhanan, R.: Kloman Meter: an EMD based tool for triaging lung diseases. In: Proc. of CCB. Springer-Nature (2020)
59. Chavan, N., Ranjan., P., Kumar, U., Shrivastav, K.D., Janardhanan, R.: EMD-based triaging of pulmonary diseases using chest radiographs (X-Rays). In: Metaheuristic Algorithms in Industry 4.0. Routledge (2021)
60. Hamming, R.W.: Error detecting and error correcting codes. The bell system technical journal **29**(2), 147–160 (1950). https://doi.org/10.1002/j.1538-7305.1950.tb00463.x
61. Ipsen, M., Mikhailov, A.S.: Evolutionary reconstruction of networks. Phys. Rev. E-Stat., Nonlinear, Soft Matter Phys. **66**(4), 6–9 (2002)
62. Jurman, G., Visintainer, R., Filosi, M., Riccadonna, S., Furlanello, C.: The HIM glocal metric and kernel for network comparison and classification. In: 2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA), pp. 1–10. IEEE (2015)
63. https://github.com/rgbnihal2/COVID-19-X-ray-Dataset
64. https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
65. Bhatia, V., Ranjan, P., Taneja, N., Singh, H., Janardhanan, R.: Early and precision-oriented detection of cervical cancer. Big Data Artif. Intell. Healthc. Appl. (2021). https://doi.org/10.1201/9781003093770-9

Mobility Analytics and COVID-19 in Greece

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Abstract This work is focused on multi-aspect analytics of epidemic data, using Greece as the use case for assessing the national outbreak and estimating the general trends and outlook of it since the beginning of the pandemic in early 2020 up to the end of 2020. Using methodologies from compartmentalized epidemic modelling, data analytics and machine learning, several insights are presented with regard to early tracking of the evolving outbreak, despite having to deal with data scarcity, inconsistencies and quality issues. It is intended to be used as a guideline for data-related challenges on producing actionable information to decision-makers during an active epidemic.

Keywords COVID-19 · SARS-CoV-2 · Greece · Data analytics · SEIR · Predictive modelling · Data restoration · Computational epidemics · Epidemic tracking

1 Introduction

In the beginning of 2020 the world landed into a pandemic of intensity and scale that has not been manifested for many decades. A global spread of flu-like infectious disease started spreading fast across countries via international travel and, although the first signs of it appeared as early as November 2019 in Wuhan, China [11], it took at least two or three more months before the rest of the world realized the seriousness of the situation. By then, it was already too late and the SARS-CoV-2

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virus had reached most of the countries world-wide, at least those with international flights.

One of the most apparent drawbacks and deficiencies of the current monitoring of epidemic diseases by authorities like ECDC (EU), CDC (USA) and WHO is in the availability of timely, accurate and information-rich epidemic data. The COVID-19 pandemic is the first such event in the era of big data, rapid dissemination and knowledge sharing at the global scale. Yet, this outbreak revealed that data availability is not guaranteed is such situations. The reporting of infected cases presents significant challenges for several reasons, including data inconsistencies, delays, saturation of health infrastructure, etc.

A full century after the Spanish flu pandemic (1918–1920) that infected 500 million people, a third of the world's population at the time, and resulted in 50 million fatalities, the COVID-19 pandemic exhibits four major differences:

- International travelling, especially via flights, is perhaps the most crucial multiplier in the spreading of the disease. Before the virus was even isolated for study, it reached every major international airport on the planet, infecting many thousands of unaware travellers.
- Modern societies are organized mostly in urban grids and mega-cities, resulting in high-density populations in relatively localized areas. This is the second most significant factor regarding the spreading of highly infectious diseases and an important societal change from what was the situation a century ago.
- Scientific knowledge and medical resources are now vastly superior to what was available a century ago, at least for most countries.
- Current technology enables the gathering, processing and analysis of huge amounts of data at a planetary scale. Within hours at most, every new evidence, laboratory result and scientific breakthrough about the new virus was disseminated via the Internet, mostly in open-access papers and data repositories.

While the first three items characterize modern societies and dictate the current requirements and constraints when dealing with such pandemics, the forth item constitutes one of the most important mitigation factors and scientific tools to achieve such a goal. Although each epidemic or pandemic is different from the others, there is now a significant body of knowledge with regard to the data-aware and data-driven epidemic monitoring of it, ranging from country-wide statistics and trends to high-resolution regional risk assessments and tracking of human mobility. These novel capabilities constitute not only a predictive tool for evaluating the status of the crisis, but also the inherent characteristics of the pathogen and how it spreads. This second function became more evident in this current pandemic, with thousands of research teams processing world-wide epidemic data, running computational experiments and estimating the true nature of the SARS-CoV-2 virus before even the first genome studies were available.

In this chapter, the data-driven analysis of the SARS-CoV-2 pandemic is addressed via various approaches of gradual complexity and refinement. In particular, using Greece as the main use case, the epidemic is analysed at the national level under the scope of different viewpoints:

1. Compartmentalized SEIR-like modelling: This is the standard, well-established way of tracking the evolution of an infectious disease using a well-defined dynamic system of equations and employing several assumptions about how it behaves in distinct states or 'compartments'.
2. Machine learning modelling: Having realistic predictive analytics for the epidemic requires the lifting of ad-hoc assumptions and simplifications of the underlying dynamics that describe the real-world process. Machine learning enables the design and implementation of purely data-driven models that approximate this process with high accuracy and predictive value.
3. Human mobility analytics: Since the spread of flu-like highly infectious diseases depends mostly on human activities, social interactions and population density, mobility tracking in residential areas, workplaces, travel hubs, etc., is inherently a crucial indicator and in some cases even a predictor in relation to epidemics.

Greece is a perfect example for describing the three approaches, each of which has specific advantages and difficulties in actual implementation. More data usually mean more options towards human mobility analytics and Machine Learning modelling, but on the other hand this is not easy to obtain in the early phases of an outbreak. Similarly, human mobility data and urban flows, e.g., transportation of passengers in buses and metro stations, are now more readily available than accurate epidemic data at a regional level, but only indicative (indirect) of what is happening or is about to happen regarding the evolution of the outbreak.

The rest of the chapter is organized as follows: Sect. 2 describes the challenges and drawbacks related to the availability of epidemic data; Sect. 3 summarizes the standard compartmentalized epidemic models and presents its application to Greece; Sect. 4 provides a quick overview of approaches from signal processing, adaptive filtering and Machine Learning in general; Sect. 5 describes the aspect of human mobility data in the scope of the SARS-CoV-2 pandemic; subsequently, Sect. 6 describes how these data can be used in association with epidemic modelling and analytics; finally, Sect. 7 summarizes the conclusions and lessons learned.

2 Coping with Degraded Data Quality and Availability

History has shown that the close tracking of an epidemic outbreak, especially at its early stages, is hard. Regardless if it is a small-scale event of a new variant of a known virus or a global-scale pandemic that spreads across countries within weeks, there is significant time between the onset of the disease, the first confirmed detections, the proper epidemic monitoring and, finally, the systematic logging of detailed, reliable data from the healthcare workflow.

There are inherent difficulties in early detection of new strains or completely novel viruses, mostly due to the lack of readily available reliable methods of tracking a highly infectious disease in the general population (time is needed before the genome of the virus is analysed, delayed reporting of confirmed infections, deaths and recoveries, undetected cases of infected people, etc.). A highly contagious disease like the Spanish flu may be affecting a huge portion of the general population but remain largely undetected if the symptoms and escalation are very mild, while more subtle outbreaks like with the ebola virus are clearly evident due to its lethality, yet much 'slower' with regard to spreading rates.

In data analytics for epidemic modelling, these factors are manifested in the form of data quality degradations of various types, ranging from partial time inconsistencies and noise factors to large portions of missing data or even complete lack of some categories of them [20]. In these cases, the modelling approach has to be adapted, reconfigured and designed specifically to cope with such deficiencies, employing both data restoration and proper selection of modelling methods, capable of providing the inputs and tools required to reach the goals that are usually two-fold: (a) provide insights about the outbreak and, indirectly, the inherent properties of the virus; and (b) provide some level or short- or long-term prediction regarding the evolution of the outbreak, in order to improve the decision-making process and mitigation planning.

The following sections provide such insights for epidemic data deficiencies, modelling and restoration methods, using the SARS-CoV-2 epidemic in Greece as the use case. Early stages of the outbreak, i.e., end of February to end of April 2020, are examined in terms of modelling the exponential growth of infections, deaths and recoveries, and these quantities are revisited a few weeks later, when data deficiencies start becoming even more evident. Restoration methods and subsequent actions can be considered as the necessary data pre-processing stages before the analytical methods for epidemic modelling, which are presented in subsequent sections further on.

2.1 Infections, Deaths, Recoveries

Using the $I(t)$ data series the following exponential formulation can be designed according to Eq. (1) [11]:

$$I(t) \approx e^{a-be^{-ct}} \tag{1}$$

where a, b, c are the function parameters. Their best-fit optimal values in the least-squares (LSE) sense [28] and the 95% confidence intervals for Greece are presented in Table 1. The first set of parameters (second column) refers to the best-fit values with data up to April 14th [11], while the second set (third column) refers to the updated best-fit values including all data up to May 3rd. It is clear that the composite exponential growth model is valid throughout this period with minimal updates to the best-fit parameters.

Figure 1 presents the difference between a 'naive' exponential $y(t) = e^{cx(t)}$ (red) with only one parameter and the good fit ($R^2 = 0.992$, RMSE $= 0.017$) of Eq. (1) (magenta). In the second case it is clear that the function design, i.e., an

Table 1 LSE-optimal function parameters in Eq. (1) for Greece. Upper half refers to data up to April 14th, lower half refers to data up to May 3rd

Parameter	Apr. 14th	May 3rd
a	8.097 (7.974, 8.221)	7.986 (7.941, 8.030)
b	8.722 (8.420, 9.024)	8.787 (8.517, 9.058)
c	0.064 (0.060, 0.068)	0.068 (0.065, 0.070)

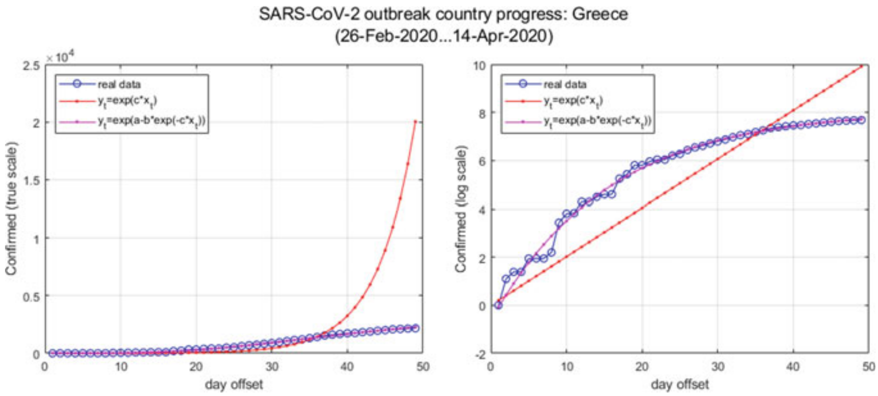

Fig. 1 'Naive' exponential $y(t) = e^{cx(t)}$ (red) with only one parameter and the good fit of Eq. (1) (magenta) for Greece. ($R^2 = 0.992$, RMSE = 0.017)

exponentially saturating formula, as well as a linear error weighting that is applied towards the more recent date range, provides the very robust set of optimized parameters that Table 1 presents. It should also be noted that, as the $I(t)$ becomes more linear due to the gradual slow-down of the national outbreak, the exponential factor c in Eq. (1) and Table 1 converges to zero and factors a and b increase, i.e., the value of $I(t)$ asymptotically approaches its upper threshold as it crossed well inside phase 5a of the epidemic and moves towards its 'peak'.

One thing that is clearly evident from the publicly available epidemic data for Greece, especially for the period after mid-April, is the severe delay in reporting the recovered $R(t)$ daily values. This constitutes a major issue in terms of data quality and, in turn, create significant difficulties in producing accurate and well-fitted epidemic models like SEIQRDP which depend heavily on $I(t)$, $D(t)$ and $R(t)$. This is a common observation in large-scale epidemics especially during in the period close to the peak of infections, mostly due to the rapidly evolving situation and the inherent delays in registering these numbers in official data reports.

In order to cope with such quality degradation of the epidemic data, an additional pre-processing step was implemented in this work for $R(t)$ reconstruction. More specifically, the overall fatality rate against confirmed cases is estimated well within the global values from other countries with similar incident intensity (cases per 100,000 of population) and COVID-19 testing policies [11]. Therefore, since all

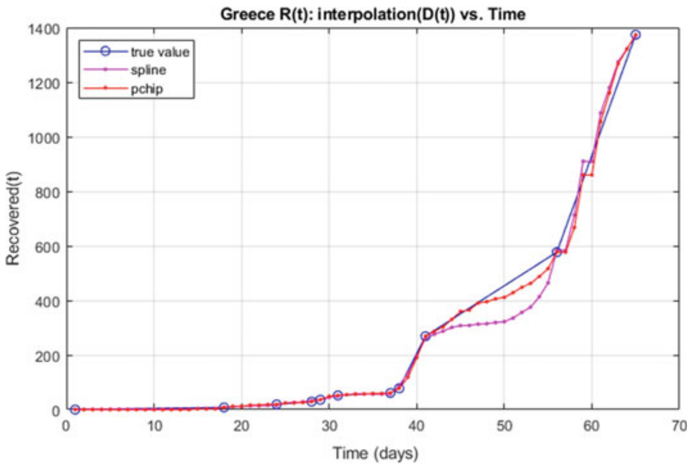

Fig. 2 Interpolation $\widehat{R}(t)$ of Recovered $R(t)$ against time (t)

Deaths $D(t)$ are confirmed and logged with proper procedures in hospitals, these can be reasonably considered a reliable baseline for both $I(t)$ and $R(t)$ assessment in terms of data quality, under-reporting rates and subsequent missing values. It should be noted that active infections are calculated as $a.I(t) = I(t) - \widehat{R}(t)$, i.e., a reliable estimation of $R(t)$ is still required even if $I(t)$ (cumulative) is accurate. In practice, every single-day official reporting of $R(t)$ is used as a reference point and high-quality interpolation against t, , specifically a spline-like piecewise cubic Hermite interpolating polynomial ('pchip') [10, 13], is employed for estimating the intermediate missing values for $R(t)$. Additional interpolation options were assessed for the same process, including $D(t)$ instead of t as the series baseline, i.e., estimate via daily deaths which is a relatively reliable data series. The 'pchip' interpolation was also compared and confirmed as superior from quadratic spline, in terms of variability from the reference baseline of piecewise linear. Figure 2 presents the interpolation process of $\widehat{R}(t)$ directly against time (t), illustrating the reference points (circles) interpolated with linear (blue), quadratic spline (magenta) and 'pchip' (red) functions; the third is chosen in this work as the best interpolator for its shape-preserving properties [25].

2.2 *Under-Reporting of Infections ($I(t)$)*

One of the most discussed issues regarding the outbreak in Greece is the under-reporting of infections $I(t)$ and how this affects the epidemic models, as well as the confidence in planning the mitigation policies. It has to be recognized, assessed in terms of magnitude and addressed via proper pre-processing within the predictive models. One such pre-processing step is the restoration of $\widehat{R}(t)$ as described previously.

It has been accepted by state officials that the under-reporting of $I(t)$ in Greece may be up to 20:1 (only 1 in 20 infections registered) or more, given the numbers from other countries and the targeted-only tests in Greece. In the update on April 14th [11], separate SEIQRDP models were evaluated with different assumptions regarding the extent of the under-reporting of $I(t)$.. According to those models, the projected dates of peak infections ranged from April 15th to May 5th, associated to no under-reporting ($f^I_{low} = 1.0$) up to a ratio of almost 1:10 ($f^I_{high} = 9.5$) for under-reporting, respectively. The availability of more recent epidemic data up to May 3rd well beyond the actual peak of $I(t)$ as described previously enable the revisiting of those projections and, hence, the validity of the associated under-reporting assumptions. More specifically, the actual peak date of 20–21 of April falls between the cases April 16th ($f^I = 1.08$) or April 25th ($f^I = 4.5$). By a rough linear regression (LR) estimation, this translates to $2.60 \leq f^I \leq 2.98$, i.e., indicating under-reporting level for $I(t)$ no more than 1:3. Additional hints regarding the under-reporting can be investigated via the Deaths $D(t)$ and ICU used compared to the infections $I(t)$ and active infections $a.I(t)$, respectively.

3 Standard Epidemic Modelling: SIR/SEIR

The mathematical modelling of epidemics has been a very active research field for decades, even before sources with detailed data were available. By far, the most popular and well-established approach is the family of *compartmental epidemic models*, originally developed as far back as 1920s. Their common characteristic is the base assumption of having a target population partitioned in *compartments* that are homogeneous in all relevant properties (e.g., sex, age, underlying pathologies, etc.) and there are direct interactions between them. The three basic compartments are S = 'susceptible', I = 'infectious' and R = 'recovered', assuming insignificant rate of deaths and permanent immunity after recovery. Variants of this SIR base model include a D = 'deaths' compartment (SIRD), E = 'exposed' compartment (SEIR, SEIRD) for introducing an incubation period, Q = 'quarantined' compartment (SEIQRD, SEIQRDP) for separating the already isolated confirmed/possible carriers, etc. The SIR-like models, along with more recent SEIR-like variants, are still used as the baseline for comparing other approaches to epidemic modelling. These are usually based on Sequential Monte Carlo [24, 31], Markov Chain Monte Carlo (MCMC) or Markov Chain quasi-Monte Carlo (MCQMC) [7, 17, 29], Hidden Markov Models (HMM) [3, 4, 27, 30], etc., each posing other assumptions, advantages and drawbacks—most commonly the availability or not of a significant amount of epidemic data upon which they are to be trained.

The SEIR-like epidemic modelling is closely related to the Lotka–Volterra system of equations [18], developed in the 1910s to describe the evolution of dynamic systems via differential equations. They constitute an example of the more generic Kolmogorov model [6, 9] which can describe the dynamics of ecological systems with predator–prey interactions, competition, disease, etc.

Based on recent models that are already being tested with COVID-19 data from China and other countries, the current work explored the (still scarce) epidemic data for Greece via the generic framework of a SEIQRDP model setup [21, 22]. The additional P = 'insusceptible' corresponds to a fraction of the general population (if any) that, even when exposed to the virus, cannot become 'infected' and, thus, does not enter the E compartments and stays outside the 'pipeline' of the epidemic. Each interaction between the SEIQRDP compartments is governed by a scalar parameter that governs the way fractions of each subset is 'transferred' to another, e.g., from 'infected' to'recovered'. Figure 3 illustrates the SEIQRDP model and the meaning of each parameter. The internal structure of the model, i.e., the interactions that describe the dynamics of the system, is formulated by Eq. (2) through Eq. (8).

$$\frac{dS(t)}{dt} = -\beta \frac{S(t)I(t)}{N} - \alpha S(t) \tag{2}$$

$$\frac{dE(t)}{dt} = \beta \frac{S(t)I(t)}{N} - \gamma E(t) \tag{3}$$

$$\frac{dI(t)}{dt} = \gamma E(t) - \delta I(t) \tag{4}$$

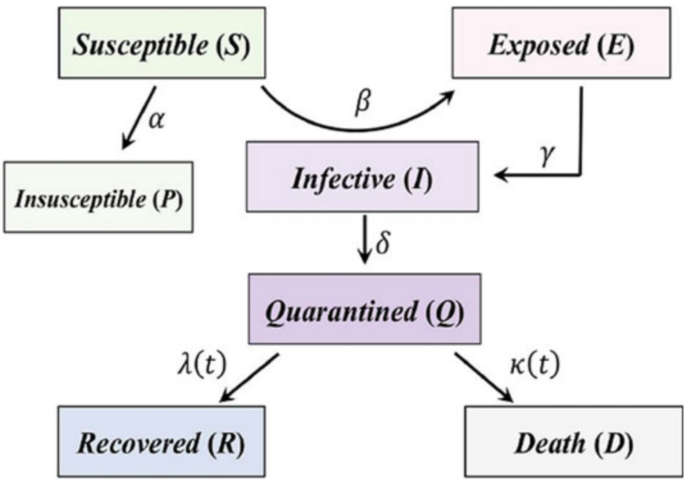

Fig. 3 The block diagram of the SEIQRDP model and its parameters

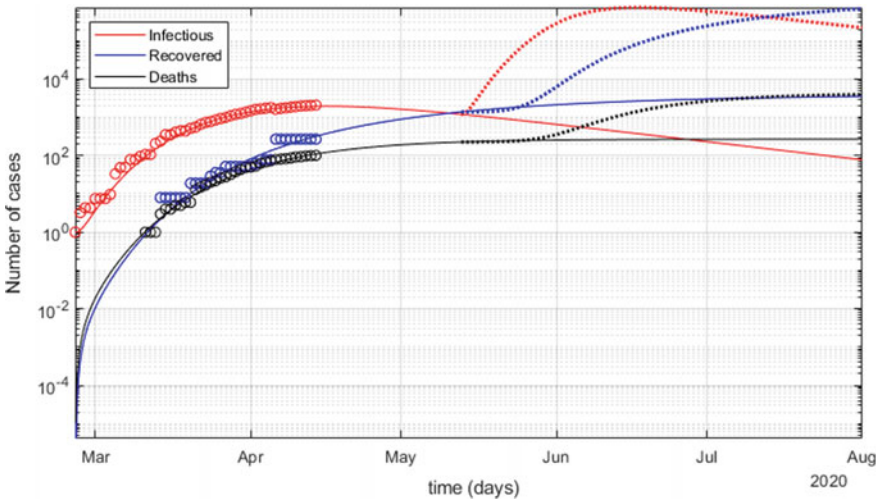

Fig. 4 SEIQRDP best-fit model (points) and its projection (lines) for marginally (1.08:1) under-reported $I(t)$, $D(t)$ and $R(t)$ until August (2020) in logarithmic scale

$$\frac{dQ(t)}{dt} = \delta I(t) - \lambda(t)Q(t) - \kappa(t)Q(t) \tag{5}$$

$$\frac{dR(t)}{dt} = \lambda(t)Q(t) \tag{6}$$

$$\frac{dD(t)}{dt} = \kappa(t)Q(t) \tag{7}$$

$$\frac{dP(t)}{dt} = \alpha S(t) \tag{8}$$

Each of the parameters of SEIQRDP model in the block diagram of Fig. 3 and the corresponding system of differential equations provide very important hints regarding the dynamics of the underlying system, i.e., the evolution of the epidemic that the model describes, given enough data are available as ground truth.

Based on the compartmentalized SIR/SEIR approach, a SEIQRDP model was designed and trained using the $I(t)$, $D(t)$ and $R(t)$ data series for Greece, from end of February to early May 2020. The purpose of this work was to re-estimate the general properties of SARS-CoV-2 virus and the COVID-19 outbreak on the national level, in order to: (a) confirm that the available data series are adequate and their evolution is in accordance to the research outcomes from other countries and on world-wide level; and (b) estimate the progress of the outbreak on the mid-/long-term level, specifically for the epidemic phases, the expected peak date and magnitude, etc.

Figure 4 presents the best-fit solution of the SEIQRDP model (points) and its projection (lines) until August (2020) in logarithmic scale, using a standard LSE solver [28] for iterative matching of the predicted trajectories to the real data. The dotted line in Fig. 4 illustrates the onset of a subsequent surge of the outbreak if all the mitigation measures (quarantine) was to be deactivated immediately (April 15th).

Table 2 presents the values for all the SEIQRDP parameters for the best-fit solution. Given the estimated under-reporting of confirmed cases $I(t)$ in Greece during that period, two additional scenarios were tested besides the 'minimal' scenario: one for the medium estimation of 4.5:1 and one for the high estimation of 9.5:1. The best-fit solutions for the corresponding SEIQRDP model of all three scenarios presented comparatively. It is worth noting that the only major difference between the three solutions is with the λ parameter, i.e., the rate between 'quarantine' and 'recovered' compartments (see Fig. 3).

Summarizing the SEIQRDP best-fit solutions for the first period of the national epidemic, including various scenarios of infections under-reporting, estimations of peak $I(t)$ dates for Greece are presented in Table 3. Note that, given the epidemic phase uncertainty due to the still limited data series, no exact value estimations are presented for $I(t)$. Nevertheless, the goodness-of-fit of the SEIQRDP solutions provides a valid 'explanation' for the dynamics of the national epidemic during that period, i.e., the interaction between the compartments. Thus, the overall shape and scale of the corresponding curves can be considered as safe for general assessments, including peak $I(t)$ dates.

Table 2 LSE-optimal SEIQRDP model parameters in Eq. (2) through Eq. (8) for Greece (26-Feb-2020 to 14-Apr-2020), minimal ($\rho = 1.08$), medium ($\rho = 4.5$) and high ($\rho = 9.5$) under-reporting of infections

SEIQRDP parameter	Minimal ($\rho = 1.08$)	Medium ($\rho = 4.5$)	High ($\rho = 9.5$)
α	0.1030	0.1156	0.1180
β	3.0000	3.0000	3.0000
γ	0.1186	0.1917	0.2435
δ	0.0352	0.0067	0.0013
λ	2.9986	0.5296	3.0000
κ	0.0468	0.0380	0.0241

Table 3 SEIQRDP projections for Greece based on the currently available epidemic data (26-Feb-2020 to 14-Apr-2020), for various scenarios of infection under-reporting

Under-reporting	Peak $I(t)$ date
Scenario for $I(t)$	–
None (1.0:1)	15-Apr
Marginal (1.08:1)	16-Apr
'Low' (4.5:1)	25-Apr
'High' (9.5:1)	5-May

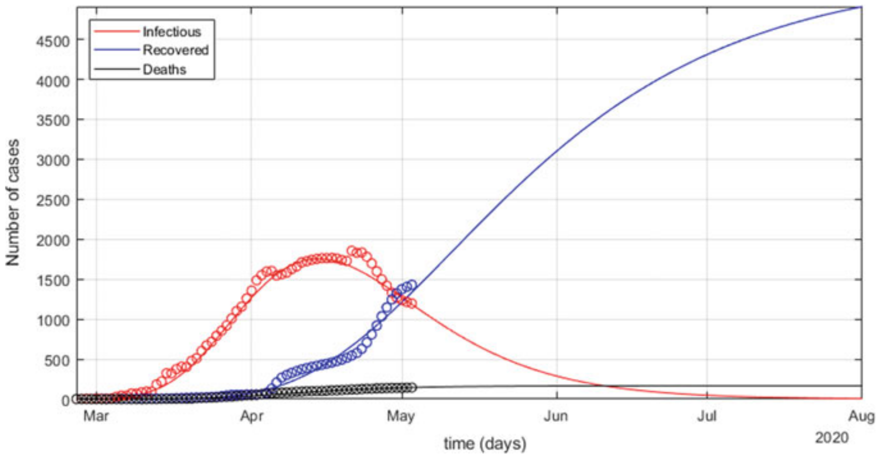

Fig. 5 SEIQRDP best-fit model (points) and its projection (lines) for $I(t)$, $D(t)$ and $R(t)$ until August (2020) in linear scale

Incorporating further data during the months that followed, the SEIQRDP model was updated on a daily basis. Figure 5 presents the best-fit solution of the SEIQRDP model (points) and its projection (lines) until August (2020) in linear scale.

Table 4 presents the values for all the SEIQRDP parameters for the corresponding best-fit LSE solution. The second column contains the values estimated in the first update (April 14th), while the third column contains the values estimated with data up to and including the second update (May 3rd). It should be noted that, due to the fact that much more data were available in the second compared to the first update and a recovered version $\widehat{R}(t)$ was used, the current SEIQRDP model fit does not include any inflation factor for $I(t)$ for addressing under-reporting effects. Similarly to the exploration of different under-reporting scenarios for infections, the most notable difference between the two best-fit values is with the 'cure rate' λ parameter. The latest value can be considered more reliable than the earlier one, since it is estimated based on more epidemic data and reconstructed $\widehat{R}(t)$.

Based on the additional epidemic data available up to May 3rd and more reliable estimation of $\widehat{R}(t)$, the SEIQRDP model fit provided an even better description of

Table 4 LSE-optimal SEIQRDP model parameters in Eq. (2) through Eq. (8) for Greece (26-Feb-2020 to 3-May-2020), with no inflation factor for $I(t)$ under-reporting and reconstructed $\widehat{R}(t)$

Parameter	Apr 14th	May 3rd
α	0.1030	0.0905
β	3.0000	3.0000
γ	0.1186	0.1114
δ	0.0352	0.0638
λ	**2.9986**	**0.0263**
κ	0.0468	0.0679

the outbreak characteristics in Greece compared to the April 14th update. The model essentially confirms the estimations of the outbreak peak regarding the projected dates around April 19th from very early on, even when only the first 7–10 days of April data were becoming available. The peak was realized on April 20th with $I(t) = 1,860$ according to the actual reported $R(t)$.

Regarding the under-reporting of infections $I(t)$, government officials have stated in formal briefings that it might be up to 20:1 (only 1 in 20 infections registered) or more, at least during the first six months of the national epidemic, a claim that was also supported at the level of at least 6.5:1 to 10:1 by other independent studies. On May 3rd, the scientific committee stated that the true number of infections, including a large number of asymptomatic carriers, is probably around 20,000–30,000, compared to a little over 2,000 which was the officially registered number of confirmed infections at that time.

Using the revisited epidemic data from late April to early May regarding confirmed infections in Greece, and examining the SEIQRDP predictions for peak in Table 3 under the three under-reporting scenarios presented above in Table 2, a rough estimation of the actual under-reporting level can be obtained. Specifically, using a simple linear regression for the dates in Table 3 and the actual peak date for confirmed infections during that period, the corresponding under-reporting factor can be estimated between 2.60 and 2.98, i.e., indicating under-reporting level for $I(t)$ no more than 1:3.

4 Higher-Order and Spectral Modelling

For a more in-depth analysis of the basic data curves $I(t)$, $D(t)$ and $R(t)$ of the COVID-19 epidemic in Greece, the corresponding time series were investigated in terms of linear and periodic trends, i.e., analyse them into their primary frequency components [11].

One of the most important factors, regardless of the long-term approximation of the underlying system, is the analysis of the step-wise dependencies between successive data points, especially the confirmed cases $I(t)$. In statistical terms, this is done by estimating the auto-correlation in the time series for various lags, which produces a quantitative description of dependencies between dates, i.e., separated by a specific number of days. Figure 6 presents the normalized auto-correlation plot of $\Delta I(t)$ (blue), i.e., the daily increases of $I(t)$. Compared to the same plot in the status update on April 14th [11], it is evident here that the two sides of the lobe are almost entirely linear and the LR lines (red) in each side. Additionally, they seem to have become more 'flattened' compared to the reference line (green) that corresponds to the case of $\Delta I(t) = c$, i.e., for constant daily increase of $I(t + \tau) = c\tau + I(t)$. There is also a distinct narrow band in the central part, which indicates an even stronger correlation between successive values, i.e., more stable and 'linearized' evolution. This proves that, at least in asymptotic behaviour towards the current state, $I(t)$ increase in Greece was gradually becoming linear during that time period.

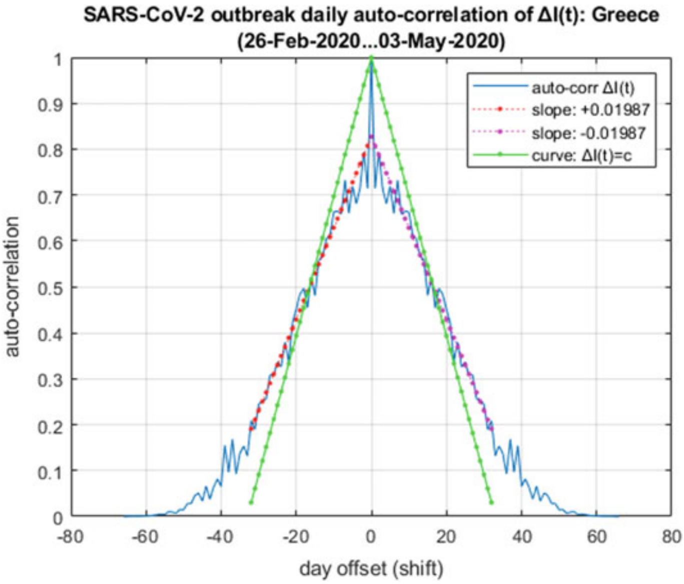

Fig. 6 Normalized auto-correlation plots of $\Delta I(t)$ (blue), the LR lines (red) in each side and the reference line (green) of the case of $\Delta I(t) = c$ (constant)

Another way to track the periodic ‘bursts’ of newly reported infections as they are reported on a daily basis is to track the changes in the short-term slope of $\Delta I(t)$. Instead of approximating the entire $I(t)$ curve as in Eq. (1) for estimating the long-term behaviour, a short-term temporal window can be used to approximate the LR slope of $I(t)$ as it progresses, i.e., the amplitude and sign of $\Delta I(t)$ changes over few subsequent days. Figure 7 illustrates such a short-term tracking of $\Delta I(t)$ via the 1st-order differential $\nicefrac{d \log \hat{b}_{1}(t)}{dt}$ of LR slope of $I(t)$,

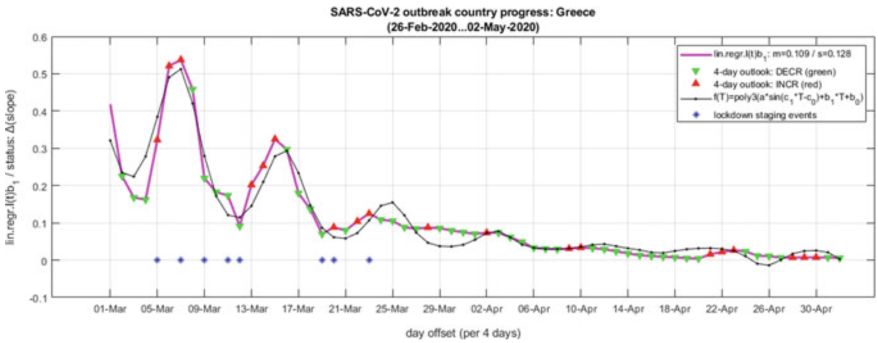

Fig. 7. 4-day sliding window slope of $\Delta I(t)$ (magenta), annotations of increasing/decreasing daily trends (red/green) and LSE-fitted approximation

where $\widehat{b}_1$ is the LR slope estimated over a four-day sliding window. In other words, the $\Delta^2 I(t)$ is estimated over a short-term sliding window of almost half a week.

The main curve (magenta) in Fig. 7 is the short-term LR slope value for $I(t)$ as it evolves; the arrow annotations indicate decreasing (green) or increasing (red) trends; the asterisks (blue) on the x-axis indicate the major events regarding the activation of mitigation measures in Greece [11]. Finally, the asymptotically fading sinusoid (black) is a LSE-fitted approximation of $g_{(t)}$ by $\widehat{g}(t)$, as defined by Eq. (9), Eq. (10) and Eq. (11).

$$g(t) = \frac{d\log\widehat{b}_1(t)}{dt} \tag{9}$$

$$\widehat{g}(t) = poly3(z(t)) = \sum_{k=0}^{3} p_k z(t)^k \tag{10}$$

$$z(t) = \alpha_2 \sin(\alpha_1 t - \alpha_0) + (\beta_1 t + \beta_0) \tag{11}$$

The LSE-optimal parameters of this multi-level approximation are presented in Table 5 with data up to and including May 3rd.

The approximation curve in Fig. 7 clearly indicates three major factors: (a) periodic trend, captured by the first part of Eq. (11) with α_i parameters, (b) linear decreasing trend, captured by the second part of Eq. (11) with β_j parameters, and (c) asymptotically fading trend, captured by the 3rd-degree polynomial of Eq. (10) with p_k parameters. The periodic trend parameters, more specifically the $\alpha_1 = 0.466$, can be translated from radians to daily temporal range via $\nicefrac{\alpha_{1}}{2\pi} = \nicefrac{t}{T}$ where $T = 68d$ is the length of the data series (May 3rd) since the first confirmed infection case (February 26th), hence yielding a period $t_{p} = \nicefrac{\alpha_{1}T}{2\pi} \approx 0.074166 T \approx 5.043d$. This is marginally smaller than the April 14th update (5.56d) and, again, coincides with

Table 5 LSE-optimal function parameters in Eq. (10) and Eq. (11) for Greece

Parameter	Optim.value	Conf.interval
α_2	0.017	(−0.011, 0.046)
α_1	0.466	(0.382, 0.551)
α_0	−9.502	(−12.980, −6.024)
β_1	−0.005	(−0.017, 0.007)
β_0	0.304	(0.073, 0.535)
p_3	4.142	(−17.500, 25.780)
p_2	3.022	(−4.415, 10.460)
p_1	0.115	(−0.490, 0.720)
p_0	0.010	(−0.019, 0.039)

the empirical data regarding the incubation (asymptomatic) period of COVID-19, estimated at 5.1–5.2 days [15, 16].

5 Human Activities and Epidemic Spread

COVID-19 is the first pandemic humanity has faced after a century with the Spanish flu. It is also the first since the globalisation and urbanisation of human societies. Within few months, the virus expanded from China's Wuhan region to the entire world, with rigorousness at the highly networked and urbanised North America and Europe. This is why the COVID-19 pandemic is described as a *tertiary domain's virus* [14].

Just like any other highly contagious flu-like virus, human mobility, social interaction and commuting are crucial factors in the evolution of the outbreak and the success of any targeted mitigation policy. This is the second viewpoint for analysing the SARS-CoV-2 pandemic, i.e., in relation to social activities, as another major driver of the epidemic modelling.

In order to control virus' expansion, most countries took mitigation measures to limit people's movements at international, national, or even regional scale. For instance, they enforced strict controls (spatial, temporal, etc.) on urban movement, whereas they prohibited international air and land connections. This was on the basis of controlled mobility, according to the *'lower and delay epidemic peak'* principle (Fig. 8).

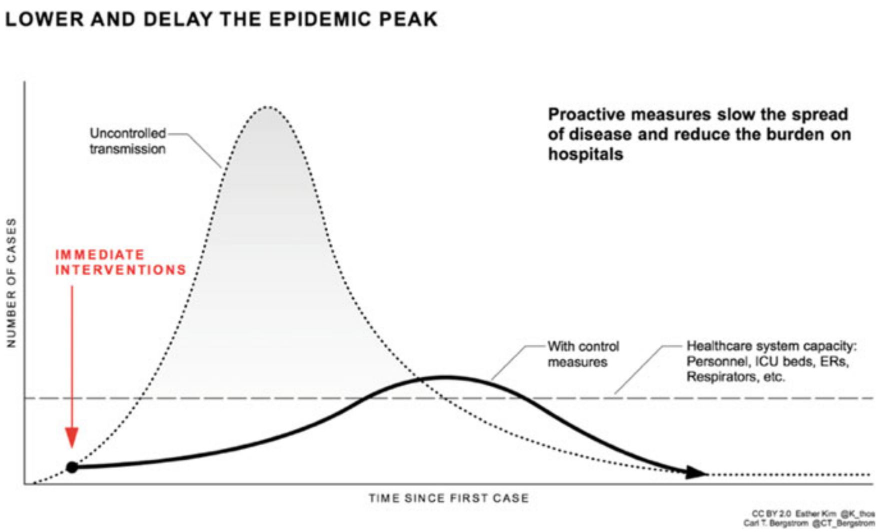

Fig. 8 The 'lower and delay the epidemic peak' principle. *Source* Ref. [5]

Table 6 Mobility shift (by activity) in example countries, three from Europe and three from eastern Asia (with and without strict mobility controls, respectively); period: Feb. 13, 2020–Mar. 27, 2021; baseline refers to Jan. 13, 2020. *Source* Google, 2021 [12]

Activity	Greece	Italy	UK	S. Korea	Singapore	Taiwan
Retail & recreation	−54%	−49%	−55%	−10%	−6%	−7%
Grocery & pharmacy	+14%	−1%	−5%	+12%	+12%	+3%
Parks	+45%	−18%	−19%	−13%	−6%	−1%
Transit stations	−45%	−47%	−54%	−15%	−12%	+1%
Workplaces	−24%	−27%	−21%	−7%	+4%	−1%
Residential	+8%	+12%	+11%	+5%	+7%	−1%

During the pandemic the majority of European countries, including Greece, kept restricting what they considered to be unnecessary movements, e.g. moving from a municipality to another or even moving by car for leisure. On the other hand, some other countries, especially eastern Asian countries, chose a different strategy focusing mainly on individual protection measures and personal diagnostic tests without strict mobility prohibitions. This differentiation is clearly presented in Table 6, where European countries present dramatic reduction of some activities, even at the level of 50%.

Additionally, several technological options were explored for the first time in such an extent, with contact tracing being probably the most celebrated approach [1, 8, 19, 23]. However, it was soon established that such solutions are deteriorated by several problems in practice, mostly due to the fact that the notion of 'contact' is very different between wireless technologies (e.g. LTE, Bluetooth, WiFi, RFID, etc.) and actual proximity in terms of human-to-human virus transmission. Nevertheless, these options are still explored and combined with other sensing modalities, like the electronic tickets used massively in public transportation within large urban regions.

In the following, we dig into the details of the temporal resolution of mobility changes, at national versus urban scale. In particular, Fig. 9 illustrates the mobility

Fig. 9 Mobility variation (by transport means) globally in Greece (left) versus Athens (right); period: Jan. 13, 2020—Mar. 27, 2021; baseline refers to Jan. 13, 2020. *Source* Apple, 2021 [2]

changes in Greece, as a whole, versus Athens, where almost half of the population of the country lives in. Two curves are illustrated in the charts referring to driving (in red) and walking (in brown); this information reflects requests for directions by Apple Maps users [2]. These charts reveal that:

- During the first wave of the pandemic (roughly from Feb. 2020 to May 2020), movement (by any means) degrades drastically. Starting from May, there is a gradual increase of movement, as expected, with a peak during the summer period.
- During the second wave of pandemic (roughly from Oct. 2020 to Mar. 2021), the lowering pattern appears again, although much smoother than the one that appeared in the first wave.

More specifically, in March 2020, strict mobility measures were enforced leading to a reduction of -80% for walking and driving, which lasted until early May 2020. After that, there was the 'summer high peak', with the extreme scores of $+140\%$ for driving and almost $+160\%$ for walking. Autumn 2020 started with an initial slow down, which was followed by a sharp decrease due to the second round of strict mobility measures. Since then and until March 2021, driving and walking remained around -40% with respect to the baseline.

Nevertheless, walking is a type of mobility that refers to a place where people are familiar with, like for instance their neighbourhood. Hence, there is a limited need for Google or Apple map apps. So, we can safely infer that walking is even more popular (compared with driving and mass transit) than what is illustrated in these figures, if we also take into account the strict distance restrictions that some governments have employed (in Greece, movement for leisure or sports was constrained within the same municipality or a 2 km distance). At urban scale, Athens had a lower peak level than Greece had at national scale.

Interesting findings arise from these data explorations: movement is more restricted in big urban centres (capitals and big cities) compared to smaller towns and countryside; this can be justified by the fact that densely populated areas enforce stricter controls and, in cases where horizontal measures were taken at national scale, they were supervised more strictly than elsewhere. Moreover, there are big differences in lifestyle between big cities and small towns or villages: in a large metropolitan area, mobility prohibition drastically changes the daily routine of people during working or leisure time, whereas in places with lower level of urbanisation, it is much easier to maintain the same routine by favouring e.g. walking or cycling instead of car driving or using public transport.

Last but not least, there is a relationship between the density of population with the number of COVID cases, which shows that this tertiary domain's virus is biased towards the big, industrialised, interconnected urban centres.

6 Correlation of Human Activity with Epidemic Spread

In order to produce useful predictive analytics, the human mobility data have to be combined and compared to the epidemic data. For Greece, mobility data from Google and Apple as presented above were available for several regional-scale geographic partitions, but with significantly later than the actual time period reported. Nevertheless, post-analysis was possible in correlation to the corrected and restored epidemic data for those same regions of Greece, synchronized in time scale.

Three regions of interest were selected for such post-analysis, on the basis of three criteria: (a) density of the native population, (b) being major transit or destination regions during the summer, and (c) availability of both human mobility and epidemic data. Figures 10, 11 and 12 present combined plots of mobility intensity (various types) and confirmed infections on a daily basis, for Attica, Aegean islands (Dodecanese, Lesbos, Samos, Chios) and Crete (Heraklion, Lasithi, Rethymno, Chania), from the beginning of the national outbreak and for a full year afterwards.

There are two milestones to be considered in these plots. The first one is the enforcement of the initial, very strict country-wide lockdown during March. As expected, this caused a sharp drop in all types of mobility trends, more evident in Attica region due to the time period (non-tourist) and predominant types of activities (mostly to and from work). The second milestone is the beginning of opening the borders during the summer of 2020, mostly in mid-July. Although there are several periods of missing data in the data series as seen in the plots, it is clear that a second, very intense surge of the epidemic starts building up exactly at that time period and evidently manifested in a much larger scale by end of September and early October.

Given that there is a delay between infections in the general population and the actual reporting after confirmation due to the incubation period of the SARS-CoV-2 virus [11], it is expected that a time shift of at least 1–3 weeks is expected between these two trends. Indeed, such an effect can be seen in the plots for the Crete region

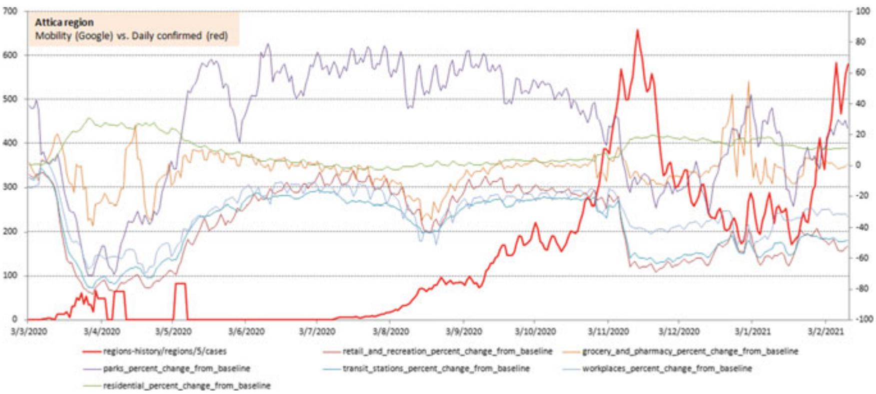

Fig. 10 Combined plots of mobility intensity (various types) and confirmed infections on a daily basis for the Attica region. *Google data* 3/3/2020–12/2/2021, 5-day moving average

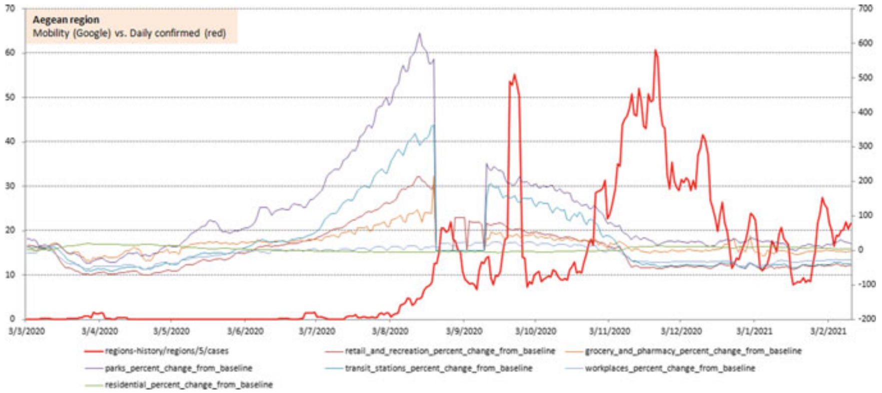

Fig. 11 Combined plots of mobility intensity (various types) and confirmed infections on a daily basis for the Aegean islands region: Dodecanese, Lesbos, Samos, Chios. *Google data* 3/3/2020–12/2/2021, 5-day moving average

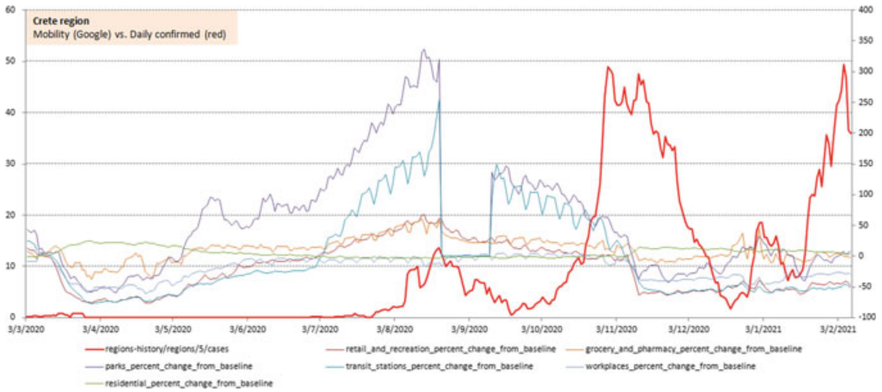

Fig. 12 Combined plots of mobility intensity (various types) and confirmed infections on a daily basis for the Crete region: Heraklion, Lasithi, Rethymno, Chania. *Google data* 3/3/2020–8/2/2021, 5-day moving average

during mid-August and, more evidently, in the plots for the Aegean islands region. Regardless of this arbitrary time shift and in order to quantify these correlations in the long term throughout a full year, simple statistical analysis can provide such hints. Figure 13 illustrates in tabular coloured format the three regions, with time period partitioned into three sub-ranges (summer 2020, late 2020, early 2021), with Pearson's correlation coefficient [26] of confirmed infections against the various types of human mobility, same as in Figs. 10, 11 and 12. The time sub-ranges correspond to the three main phases before, during and after the second surge of the national epidemic, in association to the change in behavioural patterns and the opening of the borders during the summer (tourist period).

	CORRELATION with daily confirmed (new)	retail_and_recreation_percent_change_from_baseline	grocery_and_pharmacy_percent_change_from_baseline	parks_percent_change_from_baseline	transit_stations_percent_change_from_baseline	workplaces_percent_change_from_baseline	residential_percent_change_from_baseline
Athens	1/7/20...21/8/20	-0,938	-0,942	-0,570	-0,964	-0,962	0,338
	12/9/20...20/12/20	-0,642	-0,338	-0,673	-0,604	-0,614	0,655
	21/12/20...12/2/21	0,169	-0,139	0,284	0,429	0,376	-0,506
Crete	1/7/20...21/8/20	0,769	0,713	0,790	0,785	-0,352	-0,472
	12/9/20...20/12/20	-0,414	-0,517	-0,560	-0,529	-0,430	0,385
	21/12/20...12/2/21	0,552	-0,169	-0,020	0,200	0,502	-0,748
Aegean	1/7/20...21/8/20	0,733	0,833	0,715	0,744	0,476	-0,438
	12/9/20...20/12/20	-0,622	-0,621	-0,627	-0,635	-0,652	0,652
	21/12/20...12/2/21	0,404	0,256	0,268	0,429	0,244	-0,274

Fig. 13 Pearson's correlation coefficient [26] of confirmed infections against the various types of human mobility three regions in Greece, with time period partitioned into three sub-ranges (summer 2020, late 2020, early 2021)

Based on the correlation values in Fig. 13, it is safe to draw some very important conclusions regarding the effectiveness of the mitigation policies implemented during each time period:

- During the first phase (mid-summer), there is a very strong negative correlation of the reported infections with most types of mobility, especially in the Attica region; this is expected, as Attica is a departure node for summer holidays for both natives and tourists, hence a sharp drop in regional mobility is in contrast to the underlying infections rate.
- During the same period, both Aegean islands and Crete regions show a very clear positive correlation between infections and most mobility types; this is also expected, as these regions host more than half the total non-local population (on holidays), both natives and tourists.
- During the second phase, i.e., after the tourist period, the Attica region continues to show similar but much smaller negative correlation compared to the summer, while the tourist regions shift from positive to negative as non-local populations leave and mobility drops sharply.
- In the third phase when the subsequent surge of the epidemic is escalating throughout the country, correlations shift to positive in all three regions.
- The one type of mobility that seems to illustrate somewhat adverse behaviour from the rest is associated with the 'residential' category; this is also expected, since this is associated to limited activities usually close to home, i.e., more or less complementary to the others.

It should be noted that Greece may not be a compatible example of a country in terms of geographical size, population and human flows. It is located at the south-eastern region of the EU, encompassing numerous islands in the eastern Mediterranean Sea, which makes it both a gateway for travellers and a very active destination for summer tourists. On the other hand, it has limited extent with medium/high connectivity within the country. This makes the human flow patterns inherently periodic, high-density near the peaks (July–August) and multi-national in terms of countries of origin. Other paradigms have emerged during the COVID pandemic, especially in Asia, where for example India is significantly different in all these aspects. Therefore, data-driven approaches and proper treatment of all these aspects must be taken into account in a per-country case, in order to produce realistic models with actionable outputs for the decision-makers.

In summary, the lessons learnt from the paradigm of Greece can guide the decision-makers to:

- closely monitor the border crossings and airports with respect to human flows, especially during periodic peaks (e.g. summer);
- employ extensive tracking of infections using pre-emptive screening of inbound travellers to the maximum possible extent;
- constantly model and update the mobility flows and connections within the country, in order to capture the seasonal trends in flow density (not only regarding tourists);
- employ predictive analytics with updated epidemic data, in order to have early warnings for regional possible 'hot zones', hence employing pre-emptive mitigation policies, ranging from more strict monitoring to complete but local lockdowns.

7 Conclusions

In this chapter, three main aspects of epidemic modelling were presented in detail, with Greece and its SARS-CoV-2 outbreak during 2020–2021 as a use case. Epidemic monitoring and predictive analytics are usually constrained by strong assumptions regarding the underlying system dynamics, as well as the limited availability of timely and reliable epidemic data. This usually leads to severe degradation of the accuracy and look-ahead capabilities, thus making these tools of limited value to decision-makers in formulating proper emergency response and mitigation policies.

Standard approaches and computational models like the 'compartmentalized' SEIR variants are the 'golden rule' for establishing a well-established baseline of predicting the short-term evolution and trends of an active outbreak. Moreover, having additional 'compartments', e.g. for quarantined population, further enhances the predictive value and the insights about the inherent characteristics of the disease. Human mobility analytics is a recent, very powerful modality of data that enables fine-scale mapping of dynamics and flows, especially in densely populated areas and urban nodes, associating them with commuting and spreading patterns.

Employing powerful algorithms and modern computing resources, the underlying real-world dynamics and highly volatile behaviour of the outbreak evolution can be modelled and analysed with a wide range of approaches from signal processing, adaptive filtering, applied statistics and Machine Learning. Future work should be focused on gathering more specific regional data, extensive monitoring of the human flows at the border crossings and airports, as well as on the inherent characteristics of each country paradigm, especially in geographical extent, population and mobility infrastructure, i.e., aviation, maritime and land connections.

References

1. Aggarwal, D., Page, A., Schaefer, U., Savva, G., et.al.: An integrated analysis of contact tracing and genomics to assess the efficacy of travel restrictions on sars-cov-2 introduction and transmission in England from June to September, 2020. medRxiv (2021). https://doi.org/10.1101/2021.03.15.21253590, https://doi.org/10.1101/2021.03.15.21253590
2. Apple: Mobility trends reports (2021). https://covid19.apple.com/mobility
3. Baum, L., Eagon, J.: An inequality with applications to statistical estimation for probabilistic functions of markov processes and to a model for ecology. Bull. Am. Math. Soc. **73**(3), 360 (1967)
4. Baum, L., Petrie, T.: Statistical inference for probabilistic functions of finite state markov chains. Ann. Math. Stat. **37**(6), 1554–1563 (1966). https://doi.org/10.1214/aoms/1177699147
5. Bergstrom, C.: Slow the spread—proactive control measures can reduce the epidemic peak of sars-cov-2 (2020). http://ctbergstrom.com/covid19.html
6. Brauer, F., Castillo-Chavez, C.: Mathematical Models in Population Biology and Epidemiology. Springer-Verlag (2000)
7. Chen, S., Dick, J., Owen, A.: Consistency of markov chain quasi-monte carlo on continuous state spaces. Ann. Stat. **39**(2), 673–701 (2011). https://doi.org/10.1214/10-AOS831
8. Ferretti, L., Wymant, C., Kendall, M., et. al.: Quantifying sars-cov-2 transmission suggests epidemic control with digital contact tracing. Science (2020). https://doi.org/10.1126/science.abb6936, http://science.sciencemag.org/
9. Freedman, H.: Deterministic Mathematical Models in Population Ecology. Marcel Dekker (1980)
10. Fritsch, F., Carlson, R.: Monotone piecewise cubic interpolation. SIAM J. Numer. Anal. **17**, 238–246 (1980). Mobility analytics and COVID-19 in Greece 23
11. Georgiou, H.: COVID-19 outbreak in Greece has passed its rising inflection point and stepping into its peak (2020). https://doi.org/10.5281/zenodo.3753368, https://doi.org/10.5281/zenodo.3753368, Proofreading over the previous version 1.1.00/15-Apr-2020
12. Google: Covid-19 community mobility reports (2021). https://www.google.com/covid19/mobility
13. Kahaner, D., Moler, C., Nash, S.: Numerical Methods and Software. Prentice Hall, Upper Saddle River, NJ, USA (1988)
14. Klaus, I.: Pandemics are also an urban planning problem (2020). https://www.bloomberg.com/news/articles/2020-03-06/how-the-coronaviruscould-change-city-planning
15. Kucharski, A., Russell, T., Diamond, C., et al.: Early dynamics of transmission and control of covid-19: a mathematical modelling study. Lancet. Infect. Dis (2020). https://doi.org/10.1016/S1473-3099(20)30144-4
16. Lauer, S., Grantz, K., Bi, Q., Jones, F., et al.: The incubation period of coronavirus disease 2019 (covid-19) from publicly reported confirmed cases: estimation and application. Ann. Intern. Med. (2020). https://doi.org/10.7326/M20-0504
17. Lopes, H.: Markov Chain Monte Carlo and Sequential Monte Carlo Methods in Dynamic Models and Stochastic Volatility Models. Techn. Univ. of Catalonia (2013)
18. Lotka, A.: Contribution to the theory of periodic reactions. J. Phys. Chem. **14**(3), 271–274 (1910)
19. Mokbel, M., Abbar, S., Stanojevic, R.: Contact tracing: Beyond the apps. arXiv (June 2020). arXiv:2006.04585v1, https://arxiv.org/abs/2006.04585

20. Pelekis, N., Theodoridis, Y.: Mobility Data Management and Exploration. Springer (2014). https://doi.org/10.1007/978-1-4939-0392-4
21. Peng, L., Yang, W., Zhang, D., Zhuge, C., Hong, L.: Epidemic analysis of covid-19 in China by dynamical modeling. arXiv:2002.06563v1 [q-bio.PE] (February 2020)
22. Piccolominib, E., Zamaa, F.: Preliminary analysis of covid-19 spread in Italy with an adaptive seird model. arXiv:2003.09909v1 [q-bio.PE] (2020)
23. Raskar, R., Nadeau, G., Werner, J., Barbar, R., et.al.: Covid-19 contact-tracing mobile apps: Evaluation and assessment for decision makers. arXiv (June 2020). arXiv:2006.05812, https://arxiv.org/abs/2006.05812
24. Shahtori, N., Scoglio, C., Pourhabib, A., Sahneh, F.: Sequential monte carlo filtering estimation of Ebola progression in West Africa. arXiv:1601.07606 [stat.AP] (2016)
25. Spiegel, M., Liu, J., Lipschutz, S.: Mathematical Handbook of Formulas and Tables (4th/Ed.). McGraw-Hill (2012)
26. Spiegel, M., Schiller, J., Srinivasan, R.: Probability and Statistics (3rd/Ed.). McGraw-Hill (2009)
27. Stratonovich, R.: Conditional markov processes. Theory Probab. Its Appl. **5**(2), 156–178 (1960). https://doi.org/10.1137/1105015
28. Theodoridis, S., Koutroumbas, K.: Pattern Recognition. Academic Press, 4th edn. (2008)
29. Tribble, S.: Markov chain Monte Carlo Algorithms Using Completely Uniformly Distributed Driving Sequences (Diss.). Stanford University (2007)
30. Viterbi, A.: Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. IEEE Trans. Inf. Theory **13**(2), 260–269 (1967)
31. Welding, J.: Sequential Monte Carlo Methods for Epidemic Data (PhD thesis). Dept. of Mathematics and Statistics, Lancaster University (2020)

Dynamical Modeling of Outbreak and Control of Pandemics: Assessing the Resilience of Healthcare Infrastructure Under Mitigation Policies

Hamed Kashani, Shahab Valaei Sharif, Shiva Hosseini, and Mohamad Ali Hekmatian

Abstract Enhancing the healthcare system's capacity can reduce the vulnerability of communities in the face of disease outbreaks. Dynamical modeling methods can characterize the disease outbreak patterns and the performance of the healthcare system in response to it. They can be used to develop powerful tools to evaluate the effectiveness of candidate policies and assess the resilience of the healthcare system in the face of pandemics. This chapter briefly introduces three dynamical methods applicable to the modeling of various aspects in healthcare infrastructures: Agent-Based Modeling (ABM), Discrete-Event Simulation (DES), and System Dynamics (SD). A hybrid simulation model to assess the resilience of healthcare infrastructure under pandemic mitigation policies is also presented. This model comprises three main sub-models, each of which demonstrates the application of one dynamical modeling method: (1) Disease outbreak sub-model, which uses ABM to simulate the disease outbreak, (2) Hospital performance sub-model, which uses DES to simulate the patient flow and supply of health services by hospitals, and (3) Vaccine supply sub-model, which uses SD to simulate the production and distribution of the vaccine. The model is applied to an ex-ante analysis of the COVID-19 outbreak and mitigation in the city of Izeh in Iran to showcase its capabilities.

Keywords Pandemics · Resilience · Healthcare system · Policy analysis · Dynamical modeling

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1 Introduction

The large-scale spread of infectious diseases (i.e., at the community or global level) can simultaneously impact numerous individuals. As the experience with HIV, H1N1, H5N1, SARS, and COVID-19 epidemics and pandemics show, the spread of communicable diseases can disrupt regional and national stability [1]. Pandemics can put an extraordinary burden on economic systems in various ways, such as disrupting the supply-chains of products and services and diminishing the public confidence in the financial markets [2]. The surge in demand for medical services during the pandemics can also disrupt the functionality of the healthcare systems of communities, which are tasked with controlling the casualties. A lack of resilience[1] is observed if the healthcare system cannot satisfy the demand properly. The failure of the healthcare infrastructures to respond to the surge in demand can increase the mortality rate among those infected, which will cause long-lasting or irreparable social, economic, and socio-economic damage to communities [3–5].

The occurrence of future pandemics seems inevitable due to the novel nature of viruses and their contagion patterns [1]. Therefore, public health decision-makers should use appropriate quantitative tools to assess the resilience of their communities' healthcare system in the face of pandemics. There should be adequate planning and policy-making to enhance the resilience of healthcare infrastructure and mitigate the negative consequences of probable future pandemics. The effectiveness of the adopted policies and plans depends on numerous factors, such as the characteristics of the disease and the pattern of its spread in the community, behavior of individual community members, current capacity of the healthcare system, and interventions adopted to control the disease [6]. Therefore, public health decision-makers need quantitative tools that consider the abovementioned factors and evaluate the impact of the candidate interventions designed to handle the disease outbreak and reduce mortalities before implementing them.

Dynamical modeling methods can provide the much-needed tools for assessing the performance of candidate policies and interventions designed to mitigate the negative consequences of disease outbreaks [7]. They can offer an unprecedented opportunity for decision-makers to learn from evidence and make informed decisions in real-time. Dynamical modeling methods allow building a model which is a product that represents a system of interest [8]. Dynamical modeling methods can be simultaneously used to design, implement, and run simulation models to experiment with scenarios and determine the performance of complex systems and interdependent processes [9, 10]. Policy-makers and health planners can consider several parameters (e.g., the characteristics of the disease and the pattern of its spread in the community and behavior of individual community members) and determine the impact of the preparedness and response plans and policies. Dynamical modeling also allows decision-makers to assess the resilience of the healthcare system against

[1] Resilience is defined as "the intrinsic capacity of a system, community or society predisposed to a shock or stress to adapt and survive by changing its non-essential attributes and rebuilding itself" [6].

current and future crises. This analysis provides valuable insights on improving various aspects of the healthcare system. It facilitates the implementation of appropriate preparedness and response plans that aim to enhance the performance of the healthcare system during pandemics.

Three dynamical modeling methods can simulate the dynamics of processes and events associated with the pandemics and healthcare systems' response. These methods are System Dynamics (SD), Discrete-Event Simulation (DES), and Agent-Based Modeling (ABM). Each modeling technique has specific characteristics that make it suitable for analyzing the problem from a particular perspective. By combining these modeling techniques, analytical tools that facilitate the simultaneous investigation of various aspects of a problem can be developed.

In this chapter, a hybrid simulation framework is introduced. It uses dynamical modeling methods to simulate the outbreak of a disease during a pandemic. It also stimulates the healthcare system's response considering various pharmaceutical (e.g., vaccination and treatment) and non-pharmaceutical (e.g., social distancing and lockdowns) interventions. This simulation framework comprises three main sub-models, each of which has employed one of the dynamical modeling methods mentioned above (i.e., ABM, DES, and SD). This simulation framework can be applied to evaluating the resilience of healthcare infrastructure in the face of pandemics from the perspective of supply and demand.

The rest of the chapter is organized as follows: Sect. 2 reviews the simulation framework. Next, Sect. 3 showcases an application of the proposed hybrid simulation framework to a real-world community. Section 4 shows the application results and related discussion. The testing and verification of the simulation framework are discussed in Sect. 5. Finally, Sect. 6 reviews the lessons learned and concludes the chapter.

2 Model Overview

The simulation framework presented in this chapter comprises three main sub-models: (1) an agent-based model to simulate the disease outbreak, (2) a discrete-event simulation model to characterize hospital performance, and (3) a system dynamics model to simulate vaccine supply. The structure of this simulation framework is shown in Fig. 1. As shown in Fig. 1, all of the sub-models work in harmony to simulate the pattern of disease outbreak, the healthcare system response to demand surge considering the uncertainty associated with the public's behavior, and vaccine supply. The following sections provide an overview of the sub-models and the modeling principles used to design and implement them.

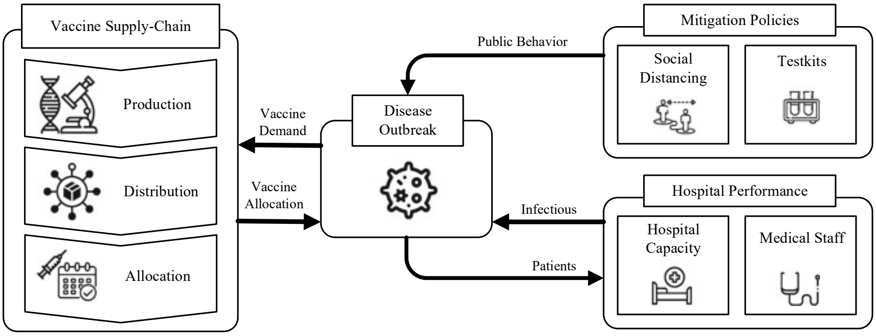

Fig. 1 Schematic overview of the proposed hybrid simulation framework

2.1 Disease Outbreak

A community is a complex and dynamic system that includes numerous individuals who behave differently in uncertain and evolving situations like pandemics. Some individuals may help prevent the transmission of the disease by adhering to social distancing measures. Others may disregard the guidelines and contribute to the spread of the disease. In pandemics, individuals' behavior leads to the emergence of complex patterns and shapes the overall trend of the disease outbreak. Infectious diseases do not uniformly affect individuals. Characteristics such as age may determine an individual's susceptibility to infections. For instance, in the case of COVID-19, it has been shown that people with underlying health conditions like diabetes mellitus, chronic lung disease, and cardiovascular problems are more likely to develop severe symptoms [11]. At the community level, the pattern of infectious disease outbreaks is affected by the population size, density, age distribution, and household size distribution [12]. In addition to social and demographic aspects, behavioral aspects such as the type and nature of daily activities can affect the pattern at which the disease spreads across the community.

Epidemiologists have harnessed the capabilities of ABM to model disease outbreaks. ABM allows capturing the infectious disease characteristics and community members' behavior, both of which contribute to the spread of the disease [13–16]. A vital feature of the ABM is its ability to consider the interactions among agents that influence how the disease spreads across the community. ABM models comprise three main elements: agents, environment, and a set of rules [17]. An agent is defined as an autonomous entity that participates in one or more interactions [18]. The main features of agents are autonomy, discernment, interaction, and decision-making [19]. Agents can interact with each other as well as the environment. These interactions follow a set of pre-determined rules and result in the behavior of each agent [20]. In the context of modeling disease outbreaks, ABM allows the characterization of the movement of infectious individuals, their behavior and interaction, and their contact rate in the community.

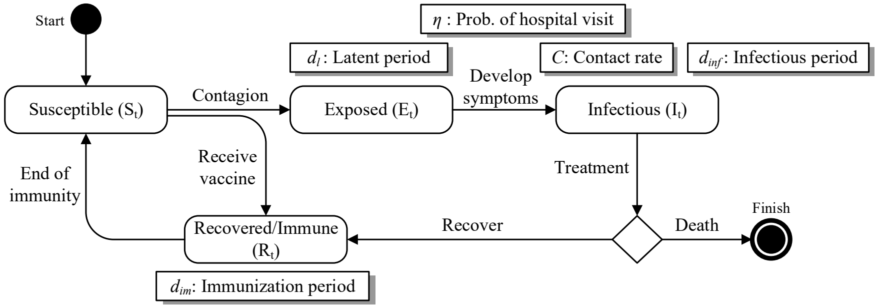

Fig. 2 State chart for agents based on SEIR model, with corresponding variables, and the transition between states

Consistent with the past studies (see, e.g., [13, 14]), the simulation framework presented in this chapter uses ABM to model the spread of the disease. The commonly used SEIR (Susceptible–Exposed–Infectious–Recovered) model (see, e.g., [2, 6, 21]) is used to develop the state diagram of the community individuals in the model. At first, agents are in the *Susceptible* state. Once contact with an infectious person is established, there is a probability that the agent's state changes to *Exposed*. The likelihood of disease transmission when contact with an infectious person occurs is referred to as *Infectivity*.

Each agent is assumed to be in contact with others daily. Only agents in the *Infectious* state can transfer the virus to other individuals. The rate of infection, $R_i(t)$, is governed by the *daily contact*, $C(t)$, and infectivity, $P_{t|c}$, as follows:

$$R_i(t) = C(t) \cdot P_{t|c} \tag{1}$$

In the outbreak sub-model, the *lockdown variable*, K, characterizes the extent to which the public adheres to social distancing guidelines. In Eq. (1), *daily contact*, $C(t)$, is determined as follows [21]:

$$C(t) = (1 - K)\lambda + K(\sigma - 1) \tag{2}$$

where, λ is pre-outbreak daily contacts, and σ is the household population. The first term in the r.h.s. of Eq. (2) shows the individual's daily contact out of the household. The lockdown variable limits the daily contacts, K. The second term encodes individuals' contacts within their households.

After a *Latent period*, d_l, the *exposed* individual develops symptoms and becomes *Infectious*. As the disease symptoms develop, the agent may decide to visit the hospital with a given probability, η. A hospital visit can happen when the agent is in the *Exposed* or *Infectious* state. The process of treatment is discussed in the following section.

Figure 2 shows the individuals' (i.e., agents') state chart and transitions between states. As Fig. 2 shows, in the aftermath of the treatment, the agent's state may be either the *deceased* or *recovered*. After recovering from the disease, it is assumed that the person remains immune to the disease during the *immunization period*, d_{im}. Moreover, if the person receives a vaccine at any time, they become immune to the disease during the remainder of the simulation.

2.2 Hospital Performance

As a critical component of the healthcare system, hospitals face a demand surge during pandemics. Hospitals must use their limited resources (e.g., beds in general or ICU wards, medical equipment, medical staff, and medicine) to treat their patients. Proper management of these limited resources can enhance the hospital's efficiency and minimize pandemic-induced life loss. Patients' flow inside the hospital is also an essential determinant of a hospital's ability to respond to the demand [22]. By managing the patient flow, a hospital can lower patients' waiting times, shorten total visit times, and reduce the staff over-time coupled while maintaining reasonable staff utilization rates.

DES is widely applied to the simulation of the behavior and performance of real-world processes, facilities, and systems [23]. It facilitates the modeling of resource management in dynamic processes. DES components include system states, events, entities, resources, activities, and relations [24, 25]. System states provide information about it at any given point of time in the simulation. Events can change system states at any time. In DES, an entity can go through various compartments. The state of an entity can dynamically change over time as it passes through the compartments. Resources provide services to the dynamic entities in the simulation. Activities happen over periods, and their duration is determined before their commencement. For instance, in the model presented in this chapter, there is an imaging lab in the hospital that, as a resource, provides services to entities (i.e., patients). At the beginning of the simulation, the state of the imaging lab is "idle." Once a patient enters the lab, its state changes to "occupied" and remains the same for the duration of the imaging process.

DES is widely used to model and analyze hospital performance [22, 26, 27]. DES capabilities and features allow the modeling of various complex, stochastic patient flow patterns. DES helps healthcare planners and managers analyze situations where resource limitation leads to the accumulation of patients in queues [28]. It enables them to evaluate various process improvement initiatives.

The modeling framework presented in this chapter harnesses the capabilities of DES to simulate the patient flow and hospital performance during a pandemic. Figure 3 shows the scheme of the hospital performance sub-model. As shown in Fig. 3, first, each person in the community may decide to go to hospitals because of developing symptoms. When an agent enters the hospital, it would be directed to *Hospital admission*, where, based on the availability of beds, it is decided whether or not the patient is admitted to the hospital. If not admitted to the hospital, the patient may return to the hospital at a later time. Alternatively, the agent may never return

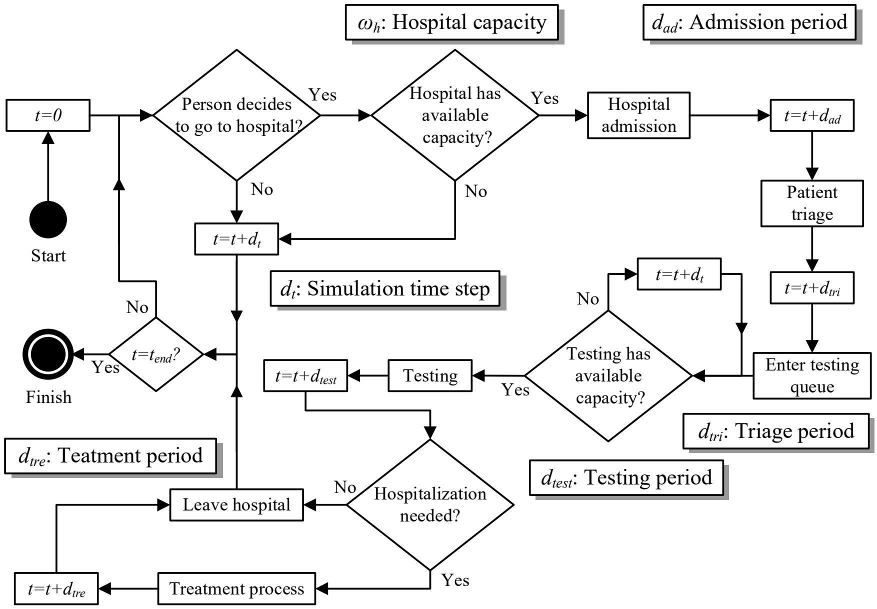

Fig. 3 Patient flow in the hospital performance sub-model and the corresponding variables

to the hospital. Next, the admitted patients move to *Triage* and *Testing* services. This process consists of checking primary and secondary symptoms using various methods such as rapid visual tests, medical imaging, and lab tests. The severity of the patient's symptoms and their underlying health conditions drive the decision about the hospitalization of a patient. Patients who are not infectious or do not have severe symptoms are sent home. Patients who need hospitalization are sent to the ICU or general wards. It is assumed that when all ICU beds are occupied, the general ward will be used to treat patients with severe symptoms. The treatment process starts after the hospitalization of a patient. As a result of the treatment, the patient may fully recover. Otherwise, the patient dies. In each simulation time step, patients who have died will be eliminated from the simulation environment.

The hospital performance sub-model also includes services that characterize the vaccination process in the hospital. Figure 4 shows that conditioned upon the availability of vaccines as determined by the vaccination sub-model, people enter the vaccine queue to receive two doses of vaccine based on a pre-determined schedule. The hospital crew administers the available vaccines to the individuals in the queue.

To quantify the resilience of the healthcare system under various scenarios from the perspective of supply/demand, the demand coverage ratio, δ, is used. It is calculated as follows:

$$\delta = \frac{D_S}{D_T} \tag{3}$$

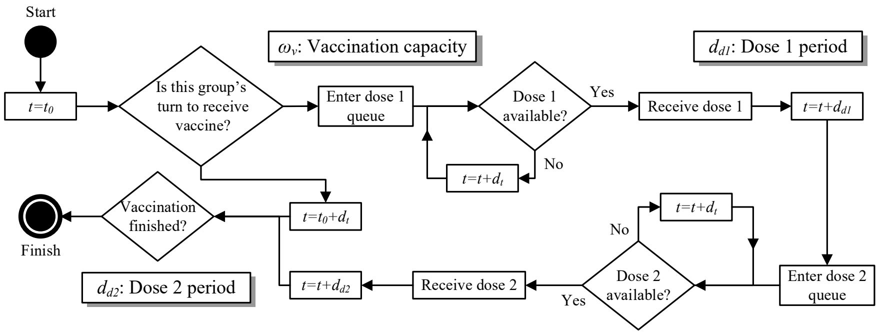

Fig. 4 Process of vaccine utilization at the hospital and the corresponding variables

where D_S is the satisfied demand for ICU and general wards, and D_T is the total demand for ICU and general wards in the hospital. When δ is equal to one, the hospital can meet the demand for hospitalization in ICU and general wards. In contrast, when δ approaches zero, the hospital cannot meet the demand, and a lack of resilience is observed.

2.3 Vaccine Supply

The vaccine supply process comprises four stages: product selection, production, allocation, and distribution [29]. At the product selection stage, healthcare planners select from a pool of candidates the vaccine will be used in the vaccination program. Vaccine production involves various uncertainties. As a result, the number and timing of vaccine supply may deviate from the planned levels. Allocation is the process of prioritizing the population to receive the vaccine. This process needs careful planning and may involve prioritizing high-risk individuals over those who are low-risk. Since there are high-transmission and low-transmission groups in the community, there are two main approaches for vaccine periodization: (1) to prioritize high-risk individuals for vaccination and directly protect them, and (2) to prioritize high-transmission individuals and indirectly protect the high-risk group [30]. Finally, the distribution stage involves delivering the vaccine from the producers to the end-users.

A derivative of systems theory, system dynamics is a method to characterize and understand the dynamic behavior of complex systems. SD recognizes the circular, interlocking, sometimes time-delayed relationships among its components of the system. The primary elements of system dynamics diagrams are feedback, accumulation of flows into stocks, and time delay. In the SD methodology, causal loop diagrams are used to capture the interactions among the system components. Variables are connected using causal links (e.g., vaccine production affects vaccine supply). By capturing interactions and consequently the feedback loops within the system, the structure of a system is represented. By characterizing the relationships among its components, the system behavior over time can be estimated. The order of a dynamic system or loop is the number of state variables or stocks it contains. Stocks are entities that accumulate or deplete overtimes. Flows are the rates at which the stocks change. Flows feed the stock during the simulation [31]. For instance, vaccine inventory could be considered as a stock variable. In this case, vaccine supply rate and vaccine consumption rate could be considered as in- and out-flows of the vaccine inventory stock, respectively. Mathematically, the relationships between model variables (i.e., stocks, flows, and auxiliary variables) are formulated as first-order differential equations to form a coupled and nonlinear system. A model may include hundreds of equations and input variables. Equations are solved simultaneously in discrete intervals of length, d_t, using the initial conditions.

Overall, SD provides a top-down view of the system, making it an ideal approach to frame and understand complex problems. Boundaries in SD models could be extended to more broad areas in comparison with other dynamical modeling methods. This is helpful to find broad factors, causal relations, and feedback loops. More specifically, SD is a powerful tool for evaluating "what-if" scenarios and various multi-level policies [32, 33]. Accordingly, SD is widely used in design and policy analysis. SD modeling approach is widely used in past research [34–39] to model and analyze the dynamic complexity of healthcare systems. The SD method has also been used to model supply-chains and inventory management systems [39–42]. Several research studies (see, e.g., [43]) have applied SD to design policies and decide about vaccine supply-chain. This study extends the generic stock management developed by Sterman [44] to model vaccine supply. The stock-flow diagram of the proposed model is shown in Fig. 5.

As Fig. 5 shows, the vaccine supply sub-model comprises three different blocks: production, distribution, and vaccine demand. The vaccine demand block calculates the number of vaccines needed over the vaccination period based on the predetermined plan. The production block simulates the process of manufacturing and shipping a vaccine. It calculates the vaccine delivery rate to a specific region by receiving the *order backlog* amount. Received vaccine orders are accumulated in *order backlog* stock. The vaccine delivery rate enters the distribution block as an input. The distribution block simulates the vaccine distribution process to the designated hospitals that administer the vaccine. This model assumes that each individual receives two doses of vaccine. Initially, once the centers receive the vaccines, they start the vaccination process using the first dose. After the interval between doses is passed, the administration of the second dose starts. The rate of administration of the second dose is dependent on the rate at which people have received the first dose. The vaccine distribution block receives as input the first and second dose consumption rates from the hospital performance model.

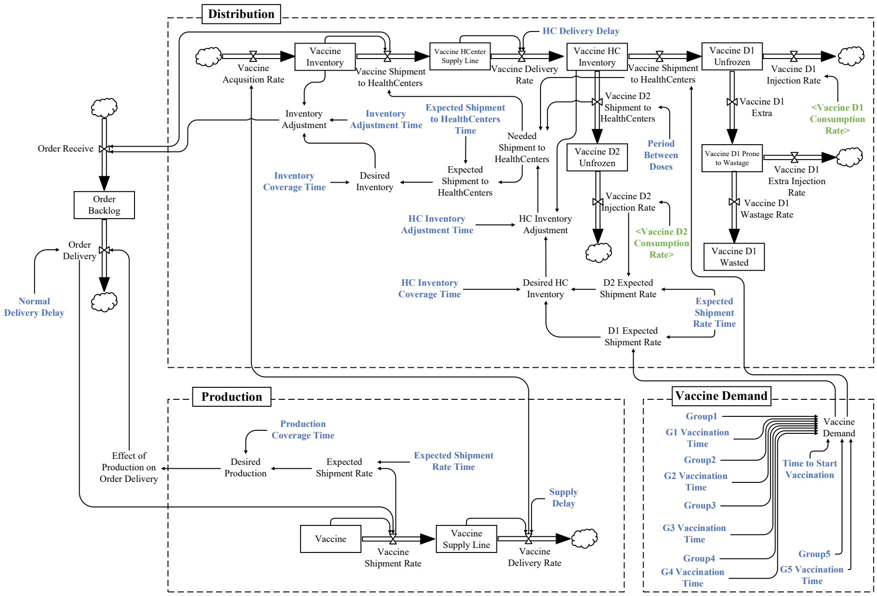

Fig. 5 Stock-flow diagram of the vaccine supply model. Variables shown in blue are model inputs from the hospital performance sub-model, while the variables shown in green are inputs from the hospital sub-model

3 Illustrative Application

In this section, the application of the proposed model is showcased using an illustrative example.

3.1 Initialization and Model Calibration

When possible, relevant literature has been used to obtain the value of several model parameters. Key model inputs, their corresponding initial values, their correspondence to each sub-model, and the reference materials used to determine their values are presented in Table 1.

To obtain the value of *initial infections*, n_{init}, *pre-outbreak daily contact*, λ, and *lockdown variable*, K, the model is calibrated using the COVID-19 statistics from the city of Izeh located in the south of Iran, with a population of 120,000. The model calibration process uses a subset of available data to obtain the value for a set of input parameters by forcing the model to satisfy pre-agreed criteria. The predicted and observed infection and mortality data for the training period are shown in Fig. 6. To assess the predictive capability of the model, the level of social distancing was set

Table 1 Key model parameters, their corresponding value, and the literature used to obtain their value

Notation	Variable or constant	Description	Value	Unit	References
Disease outbreak sub-model					
i	Infectivity	Probability of being infected in contact with an infectious person	0.06		[45]
λ	Pre-outbreak daily contact	Number of daily contacts per person before the onset of the disease	1.4	Person/Day	Calibration
d_l	Latent period	Time elapsed between exposure and the start of the asymptomatic state	U(2.5, 5)	Day	[2, 21]
d_{im}	Immunization period	Duration of immunization period for individuals	U(48, 142)	Day	
σ	Household Population	Average number of household members in the population	4.1	Person	Observed data
n_{init}	Initial Infections	Number of infections at the onset of the outbreak	0.3	% of population	Calibration
K	Lockdown variable	Level of social distancing	[0–1]		Calibration (between 0 and 1)
d_{inf}	Infectious period	Duration of being infectious for each individual	U(5, 10)		[2]
η	Prob. of a hospital visit	Probability of making a decision to go to the hospital	0.4 in "exposed" state and 0.8 in "infectious state"		Assumed
Hospital performance sub-model					

(continued)

Table 1 (continued)

Notation	Variable or constant	Description	Value	Unit	References
ω_h	Hospital capacity	Total number of hospital beds	4	Beds per thousands of population	Assumed
ω_{lt}	LabTest capacity	Total number of lab tests in the hospital	0.25	Labs per thousands of population	Assumed
ω_i	Imaging capacity	Total number of imaging labs in the hospital	0.25	Labs per thousands of population	Assumed
d_{ad}	Admission period	Duration of reception to the hospital	10	Minutes	Assumed
d_{tri}	Triage period	Duration of triage before hospitalization	U(15, 25)	Minutes	Assumed
d_{test}	Testing period	Duration of a test	U(45, 90)	Minutes	Assumed
d_{tre}	Treatment period	Duration of treatment for hospitalized patients	8.6	Day	[2, 46]
μ_1	ICU death rate	Probability of death in ICU	0.4		[47]
μ_2	General death rate	Probability of death in the general ward	0.0277		Assumed
ω_v	Vaccination capacity	Total number of available crews for vaccination	10	Crew per thousands of population	Assumed
d_{d1}	Dose 1 period	Time elapses while receiving the first vaccine dose	U(30, 60)	Minutes	Assumed
d_{d2}	Dose 2 period	Time elapses while receiving the second vaccine dose	U(30, 60)	Minutes	Assumed
Vaccine supply sub-model					

(continued)

Table 1 (continued)

Notation	Variable or constant	Description	Value	Unit	References
DS	Supply Delay	Time to transfer vaccines from production to the community inventory	2	Day	Assumed
ESRT	Expected Shipment Rate Time	Time to adjust shipment rate from production to the inventory demands	10	Day	Assumed
PCT	Product Coverage Time	Time expected that vaccine products cover the inventory demands	30	Day	Assumed
NDD	Normal Delivery Delay	Time to deliver inventory orders	2	Day	Assumed
IAT	Inventory Adjustment Time	Time to adjust the inventory level to the desired level	5	Day	Assumed
ICT	Inventory Coverage Time	Time that the inventory covers demands from health centers	15	Day	Assumed
ESHCT	Expected Shipment to HC Time	Time to adjust shipment rate from the inventory to HC demand	5	Day	Assumed
HCDD	HC Delivery Delay	Time to transfer vaccines from the inventory to HCs	1	Day	Assumed
HCIAT	HC Inventory Adjustment Time	Time to adjust the HC inventory level to desired level	5	Day	Assumed

(continued)

Table 1 (continued)

Notation	Variable or constant	Description	Value	Unit	References
ESRT	Expected Shipment Rate Time	Time to adjust injection rate in HCs to vaccination demand	7	Day	Assumed
HCICT	HC Inventory Coverage Time	Time expected that the HC inventory cover vaccine demand	20	Day	Assumed
DBD	Delay Between Doses	Waiting time to receive vaccine second dose	21	Day	Assumed
TTSV	Time to Start Vaccination	Simulation time step to start mass vaccination	Depends on the scenario	Day	Assumed

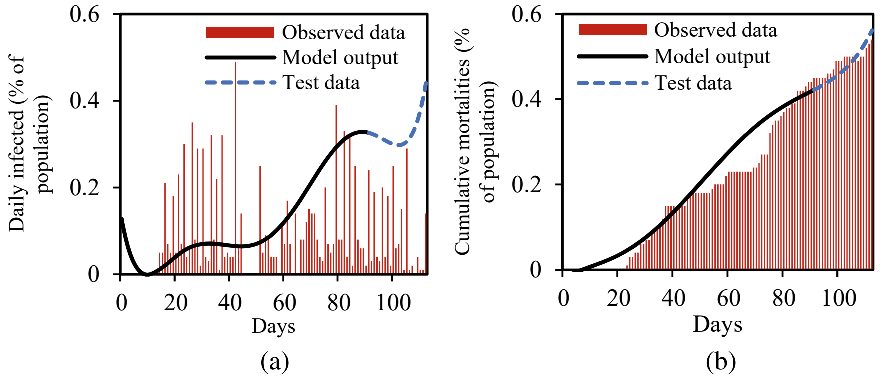

Fig. 6 **a** Observed daily number of infections versus the number of infections predicted using the calibrated model, and **b** observed cumulative mortalities versus the cumulative mortalities predicted using the calibrated model

equal to the value obtained at the end of the calibration period. The model predictions were then compared to the reported data.

3.2 Experimental Methodology

Several scenarios were simulated using the framework discussed above to assess the resilience of the healthcare system from the perspective of demand and supply. The base scenario is initiated first. It is assumed that throughout the simulation, the K variable remains constant over two-week periods. These values are 0, 0.29, 0.57, 0.19, 0.24, and 0.5 from period one to six, respectively, and remains constant throughout the rest of the simulation period. Next, the impact of enforcing social distancing measures on the disease outbreak and the performance of the hospital is evaluated. In this experiment, various levels of adherence of the population to social distancing guidelines are assumed, and the corresponding K values are used as inputs to the model. Finally, the effect of vaccine utilization on the disease outbreak and the performance of the hospital is evaluated under several scenarios. Under each scenario, people are assumed to receive two vaccines doses according to a schedule that prioritizes the medical staff and most vulnerable population groups. According to this plan, the population is divided into five groups, namely G1 to G5. The scheduled vaccination time for each group is based on the population of the group. The characteristics of each group and the scheduled period of vaccination for each group are demonstrated in Table 2.

Table 2 Characteristics of vaccination groups

Group	Description	Scheduled vaccination period (days)
G1	Medical staff	10
G2	People over the age of 60 and people with underlying health issues	20
G3	Prisoners, police personnel, military personnel, refugee camps, bank personnel, public transport staff, teachers, and school staff	20
G4	People between the age of 25 and 55	25
G5	The remaining population	25

4 Results

In this section, the results of the experiments are presented. Following the calibration and testing of the model, several scenarios were simulated over 100 days to evaluate the impact of government interventions (e.g., enforcing lockdowns) and vaccination on the disease outbreak and the hospital performance.

4.1 Enforcing Lockdown

The impact of enforcing various levels of lockdown on the disease outbreak and the performance of the hospital was evaluated. As Table 3 shows, six values were considered for the lockdown variable, K. Each value corresponds to a specific lockdown level. Associated with each lockdown level are different sets of rules on the social and economic activities the citizens can and cannot do. Figure 7 shows the simulation outcomes for this experiment. As expected, increasing the lockdown measure controls the disease outbreak, reduces the number of infections, and helps flatten the mortality curve in a shorter period (see, Fig. 7a, b).

The time-dependent demand coverage ratio for various lockdown scenarios is shown in Fig. 7c. As evident, the demand far exceeds the capacity of the hospital in

Table 3 Various lockdown levels and their corresponding K value

Lockdown level	Description	Corresponding K value
Level 1	No lockdown	0.1
Level 2	Very slight	0.25
Level 3	Slight	0.4
Level 4	Moderate	0.55
Level 5	Extensive	0.7
Level 6	Very Extensive	0.85

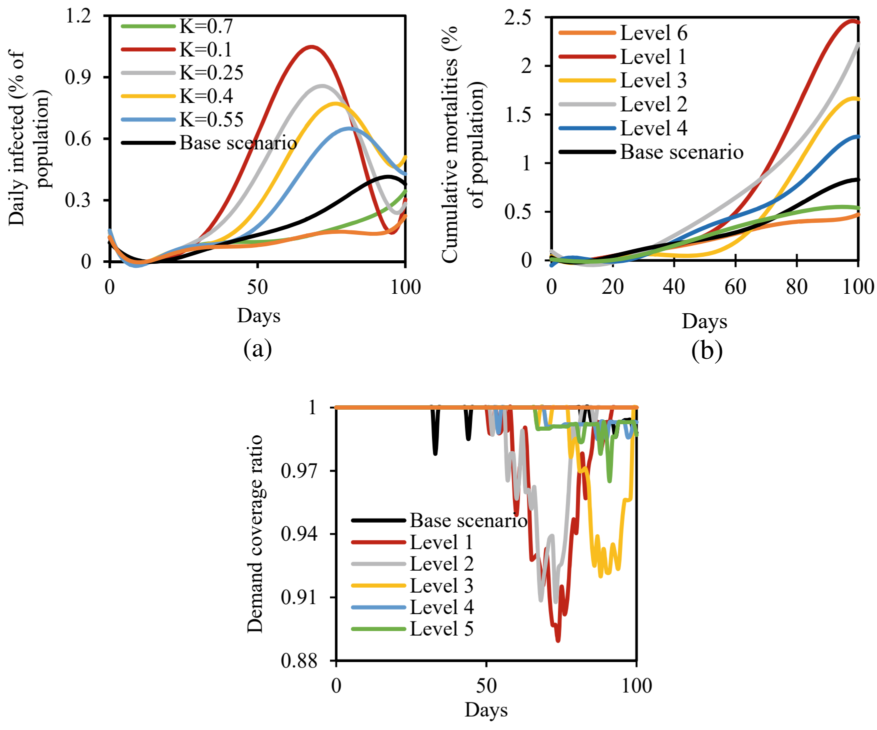

Fig. 7 The impact of lockdown level on **a** the number of daily infected, **b** cumulative mortalities, and **c** demand coverage ratio

lockdown levels of 1, 2, and 3. Therefore, in such situations, the hospitals cannot meet the hospitalization demand. In contrast, in the base scenario and the scenarios where the lockdown levels are elevated above 4, the demand coverage ratio periodically falls below one, which means that the hospitals can meet the hospitalization demand.

4.2 Vaccination

The impact of vaccination on the outbreak of the disease and the performance of hospitals was evaluated next. Due to the novel nature of the viruses that cause pandemics, the progress of various stages of the vaccine supply process (i.e., product selection, production, distribution, and allocation) is often subject to uncertainties. Due to these uncertainties, the vaccination process may not commence as planned. Accordingly, the impact of the timing of the vaccination process (i.e., the time at which the mass vaccination starts) on the outcome of the outbreak mitigation efforts was evaluated. Figure 8 shows the outcome of this analysis. The results show that the

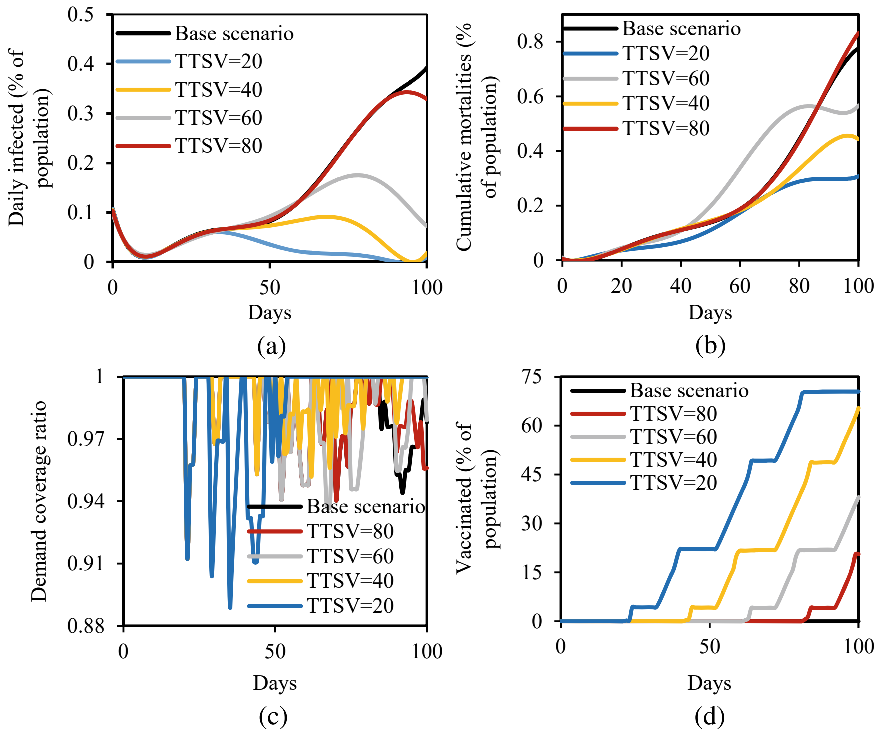

Fig. 8 Impact of vaccination timing on **a** daily infected, **b** cumulative mortalities, **c** demand coverage ratio, and **d** vaccinated population

modeling framework provides results that are consistent with the evidence. Specifically, they show that, once the mass vaccination starts, detected daily infections gradually decline. Although late vaccine utilization helps flatten the mortality and infection curves, delaying the mass vaccination process can have adverse effects. Figure 8c shows that mass vaccination reduces infections and, consequently, hospitalization demand. The demand reduction relieves the pressure on healthcare workers and increases the number of available hospital beds, which can be used to hospitalize those with severe symptoms or underlying health issues (e.g., diabetes or obesity).

In order to start the process of mass vaccination, it is required to place orders based on the pre-determined allocation plan. When the plan for vaccinating various susceptible groups is in place, the healthcare authorities order the vaccines. Figure 9 shows the state of the hospital's vaccine inventory during the simulation period. The level of vaccine inventory depends on the vaccination time, TTSV. Once initial conditions for vaccination are met, vaccine inventory will be replenished. Depending on the duration of vaccine supply processes (i.e., vaccine selection, production, and distribution), the inventory level will increase to a maximum level.

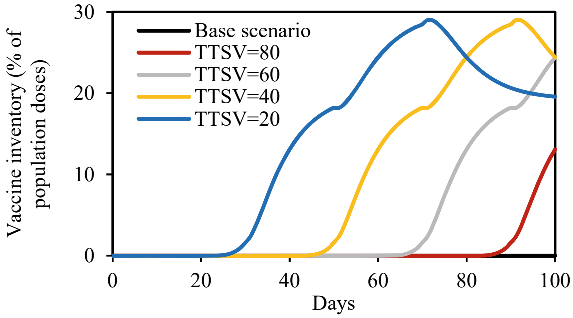

Fig. 9 Vaccine inventory levels under various scenarios

5 Verification

Several testing methods have been proposed to verify and validate simulation models [31, 34, 48–50]. The commonly used methods for verifying simulation models are dimensional consistency test, extreme condition test, behavior reproduction test, and sensitivity analysis. The dimensional consistency test involves evaluating all the variables and corresponding equations to determine whether the aggregate dimensions of the variables on both sides of the equations are identical [31]. The extreme condition test determines whether the model behaves correctly when extreme values (e.g., zero or infinity) are assigned to a given variable. The behavior reproduction test compares the modeled behaviors (i.e., model outputs) against the observed behavior. Finally, sensitivity analysis determines whether model results are significantly affected when model parameters are varied over the plausible range of uncertainty. If the model behavior does not change significantly, the confidence in the modeling is increased [38, 47]. The tests mentioned above were implemented throughout the modeling process. However, for brevity, only the results of sensitivity analysis are presented in this chapter.

5.1 Sensitivity Analysis

Sensitivity analysis can be used to examine the compliance of the simulation results with expectations. In this study, sensitivity analysis was performed on selected variables, including the number of daily contacts, λ, and hospital capacity, ω_h. Figure 10 shows that the model outputs (i.e., daily infections and cumulative mortalities are highly sensitive to λ values). Thus, a slight change in the value of λ can completely change the trend of the disease outbreak. These results highlight that the behavior that the model simulates conforms with the expectation that individuals' daily contacts play an essential role in the disease spread.

Similarly, Fig. 11 shows a slight increase in the number of available hospital beds per thousands of population in the hospital can enhance the ability of the healthcare

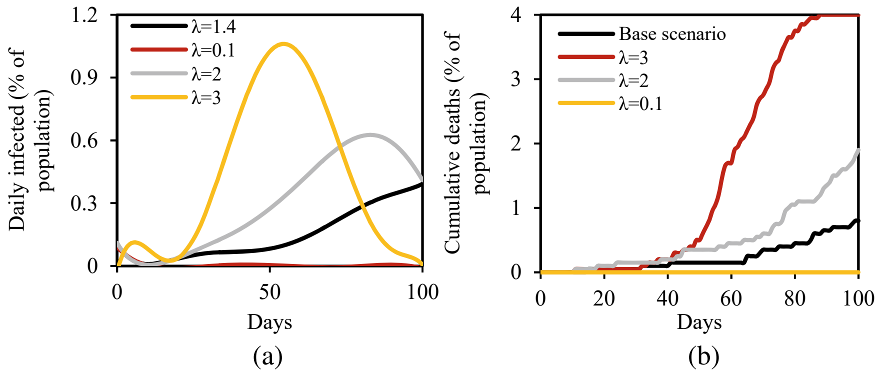

Fig. 10 Impact of the variations of the pre-outbreak daily contacts, λ, on **a** the daily infected and **b** the cumulative mortalities

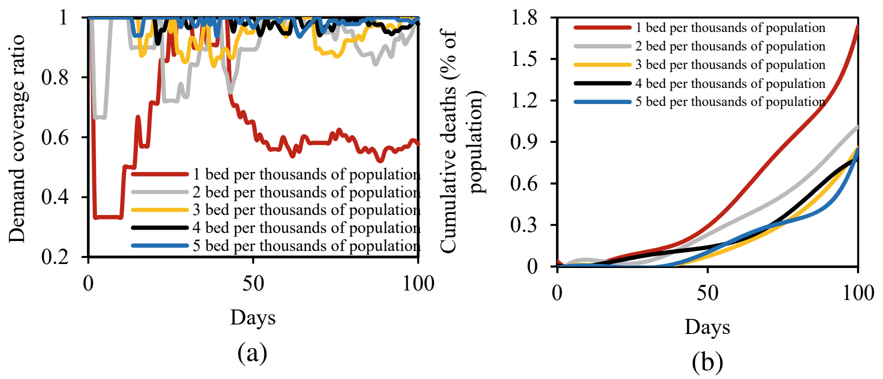

Fig. 11 Impact of the variations of the number of hospital beds on **a** the demand coverage ratio and **b** cumulative mortalities

system to respond to the demand surge and reduce the mortality rates. However, note that an increase in the hospital capacity increases the expenses, which affects the marginal value of adding more beds.

6 Conclusions

Public health decision-makers can use several pharmaceutical and non-pharmaceutical interventions to control the outbreak of infectious diseases such as COVID-19. As the experience with COVID-19 shows, abating the social and economic disruptions of a pandemic concurrent with controlling the morbidity and mortality rates is challenging. In such situations, the healthcare system becomes the frontline of response to the pandemic. Therefore, it must be adequately prepared and equipped with the necessary resources to respond to the surge in demand for medical care. Otherwise, numerous issues such as the shortage of medicine, medical equipment, and medical staff may arise, which can hinder the ability of the healthcare system to carry the significant burden caused by the spread of the disease.

To address these issues, there should be appropriate preparedness plans to enhance the capability of the healthcare system in the face of pandemics. Public health decision-makers need appropriate quantitative tools that assist them in determining the impact of various policies for responding to the outbreak and fine-tune them before their implementation. These tools should be able to model the spread of the infectious disease considering the characteristics of the disease, the behavior of the community, the performance of the healthcare system, and the behavior of other elements that are fundamental to the pandemic response (e.g., medicine supply).

This chapter presents a modeling framework that can assist public health decision-makers by quantifying the performance of the healthcare system under various plans for responding to outbreaks (e.g., lockdowns and mass vaccinations). Dynamical modeling techniques such as system dynamics (SD), discrete-event simulation (DES), agent-based simulation (ABS) modeling are used to characterize the dynamics of the disease outbreak as well as the performance of the healthcare system in the face of the demand surge. This modeling framework can consider the uncertainty associated with the behavior of the public, the nature of the disease, the performance of hospitals, and vaccination efforts. It is unique as it determines the extent of the impact of system components (e.g., community, healthcare system, and vaccine supply chain) on the observed outcome (e.g., morbidity and mortality rates). The modeling framework facilitates identifying the deficiencies of each component and an ex-ante analysis of various policies to control morbidities and mortalities (e.g., lockdown, testing, hospital capacity building, and vaccination).

References

1. Qiu, W., Rutherford, S., Mao, A., Chu, C.: The pandemic and its impacts. Health Cult. Soc. **9**, 1–11 (2017)
2. Tuite, A.R., Fisman, D.N., Greer, A.L.: Mathematical modelling of COVID-19 transmission and mitigation strategies in the population of Ontario, Canada. Cmaj **192**(19), E497–E505 (2020)
3. Cimellaro, G.P., Reinhorn, A.M., Bruneau, M.: Framework for analytical quantification of disaster resilience. Eng. Struct. **32**(11), 3639–3649 (2010)
4. Manyena, S.B.: The concept of resilience revisited. Disasters **30**(4), 434–450 (2006)
5. Jordà, Ò., Singh, S.R., Taylor, A.M.: Longer-run economic consequences of pandemics, pp. 0898–2937 (2020). Retrieved from
6. Peng, L., Yang, W., Zhang, D., Zhuge, C., Hong, L.: Epidemic analysis of COVID-19 in China by dynamical modeling (2020). arXiv preprint arXiv:2002.06563
7. Marshall, D.A., Burgos-Liz, L., Pasupathy, K.S., Padula, W.V., IJzerman, M.J., Wong, P.K., Higashi, M.K., Engbers, J., Wiebe, S., Crown, W.: Transforming healthcare delivery: integrating dynamic simulation modelling and big data in health economics and outcomes research. PharmacoEconomics **34**(2), 115–126 (2016)

8. Maria, A.: Introduction to modeling and simulation. In: Paper presented at the Proceedings of the 29th conference on Winter simulation (1997)
9. Harrison, J.R., Lin, Z., Carroll, G.R., Carley, K.M.: Simulation modeling in organizational and management research. Acad. Manag. Rev. **32**(4), 1229–1245 (2007)
10. Sokolowski, J. A. and Banks, C. M.: Principles of modeling and simulation: a multidisciplinary approach. John Wiley & Sons (2011)
11. COVID, C., Team, R., COVID, C., Team, R., COVID, C., Team, R., Chow, N., Fleming-Dutra, K., Gierke, R., Hall, A.: Preliminary estimates of the prevalence of selected underlying health conditions among patients with coronavirus disease 2019—United States, February 12–March 28, 2020. Morb. Mortal. Wkly. Rep. **69**(13), 382 (2020)
12. Aleman, D.M., Wibisono, T.G., Schwartz, B.: A nonhomogeneous agent-based simulation approach to modeling the spread of disease in a pandemic outbreak. Interfaces **41**(3), 301–315 (2011)
13. Perez, L., Dragicevic, S.: An agent-based approach for modeling dynamics of contagious disease spread. Int. J. Health Geogr. **8**(1), 1–17 (2009)
14. Venkatramanan, S., Lewis, B., Chen, J., Higdon, D., Vullikanti, A., Marathe, M.: Using data-driven agent-based models for forecasting emerging infectious diseases. Epidemics **22**, 43–49 (2018)
15. Mukherjee, U.K., Bose, S., Ivanov, A., Souyris, S., Seshadri, S., Sridhar, P., Watkins, R., Xu, Y.: Evaluation of reopening strategies for educational institutions during COVID-19 through agent based simulation. Sci. Rep. **11**(1), 1–24 (2021)
16. Silva, P.C., Batista, P.V., Lima, H.S., Alves, M.A., Guimarães, F.G., Silva, R.C.: COVID-ABS: An agent-based model of COVID-19 epidemic to simulate health and economic effects of social distancing interventions. Chaos, Solitons Fractals **139**, 110088 (2020)
17. Epstein, J.M., Axtell, R.: Growing artificial societies: social science from the bottom up. Brookings Institution Press (1996)
18. Dignum, M.: A Model for Organizational Interaction: Based on Agents, Founded In Logic. SIKS (2004)
19. Macal, C.M., North, M.J.: Agent-based modeling and simulation. In: Paper presented at the Proceedings of the 2009 Winter Simulation Conference (WSC) (2009)
20. Gilbert, N., Troitzsch, K.: Simulation for the Social Scientist. McGraw-Hill Education (UK) (2005)
21. Arenas, A., Cota, W., Gómez-Gardenes, J., Gómez, S., Granell, C., Matamalas, J.T., Soriano-Panos, D., Steinegger, B.: A mathematical model for the spatiotemporal epidemic spreading of COVID19. *MedRxiv* (2020)
22. Jacobson, S.H., Hall, S.N., Swisher, J.R.: Discrete-event simulation of health care systems. In: Patient Flow: Reducing Delay In Healthcare Delivery, pp. 211–252. Springer (2006)
23. Allen, M., Spencer, A., Gibson, A., Matthews, J., Allwood, A., Prosser, S., Pitt, M.: Right Cot, Right Place, Right Time: Improving the Design and Organisation of Neonatal Care Networks–A Computer Simulation Study (2015)
24. Banks, J.: Handbook of Simulation: Principles, Methodology, Advances, Applications, and Practice. John Wiley & Sons (1998)
25. Banks, J.: Discrete Event System Simulation. Pearson Education India (2005)
26. Melman, G., Parlikad, A., Cameron, E.: Balancing scarce hospital resources during the COVID-19 pandemic using discrete-event simulation. Health Care Manag. Sci. 1–19 (2021)
27. Reynolds, M., Vasilakis, C., McLeod, M., Barber, N., Mounsey, A., Newton, S., Jacklin, A., Franklin, B.D.: Using discrete event simulation to design a more efficient hospital pharmacy for outpatients. Health Care Manag. Sci. **14**(3), 223–236 (2011)
28. Caro, J.J., Möller, J.: Advantages and disadvantages of discrete-event simulation for health economic analyses. Exp. Rev. Pharmacoecon. Outcomes Res. **16**(3), 327–329 (2016)
29. Duijzer, L.E., Van Jaarsveld, W., Dekker, R.: Literature review: the vaccine supply chain. Eur. J. Oper. Res. **268**(1), 174–192 (2018). https://doi.org/10.1016/j.ejor.2018.01.015doi:10.1016/j.ejor.2018.01.015

30. Bubar, K.M., Reinholt, K., Kissler, S.M., Lipsitch, M., Cobey, S., Grad, Y.H., Larremore, D.B.: Model-informed COVID-19 vaccine prioritization strategies by age and serostatus. Science **371**(6532), 916–921 (2021)
31. Sterman, J.: Business Dynamics. Irwin/McGraw-Hill c2000 (2010)
32. Marshall, D.A., Burgos-Liz, L., IJzerman, M.J., Osgood, N.D., Padula, W.V., Higashi, M.K., Wong, P.K., Pasupathy, K.S., Crown, W.: Applying dynamic simulation modeling methods in health care delivery research—the SIMULATE checklist: report of the ISPOR simulation modeling emerging good practices task force. Value Health **18**(1), 5–16 (2015)
33. Marshall, D.A., Burgos-Liz, L., IJzerman, M.J., Crown, W., Padula, W.V., Wong, P.K., Pasupathy, K.S., Higashi, M.K., Osgood, N.D.: Selecting a dynamic simulation modeling method for health care delivery research—Part 2: Report of the ISPOR Dynamic Simulation Modeling Emerging Good Practices Task Force. Value Health **18**(2), 147–160 (2015)
34. Khanmohammadi, S., Farahmand, H., Kashani, H.: A system dynamics approach to the seismic resilience enhancement of hospitals. Int. J. Disaster Risk Reduct. **31**, 220–233 (2018)
35. Atkinson, J.-A., Wells, R., Page, A., Dominello, A., Haines, M., Wilson, A.: Applications of system dynamics modelling to support health policy. Public Health Res. Pract. **25**(3), e2531531 (2015)
36. Currie, D.J., Smith, C., Jagals, P.: The application of system dynamics modelling to environmental health decision-making and policy-a scoping review. BMC Public Health **18**(1), 1–11 (2018)
37. Rwashana, A.S., Williams, D.W., Neema, S.: System dynamics approach to immunization healthcare issues in developing countries: a case study of Uganda. Health Informatics J. **15**(2), 95–107 (2009)
38. Lyons, G.J., Duggan, J.: System dynamics modelling to support policy analysis for sustainable health care. J. Simul. **9**(2), 129–139 (2015)
39. Samuel, C., Gonapa, K., Chaudhary, P., Mishra, A.: Supply chain dynamics in healthcare services. Int. J. Health Care Qual. Assur. (2010)
40. Angerhofer, B.J., Angelides, M.C.: System dynamics modelling in supply chain management: research review. In: Paper presented at the 2000 Winter Simulation Conference Proceedings (Cat. No. 00CH37165) (2000)
41. Fontes, C.H.d.O., Freires, F.G.M.: Sustainable and renewable energy supply chain: a system dynamics overview. Renew. Sustain. Energy Rev. **82**, 247–259 (2018)
42. Kumar, D., Kumar, D.: Modelling rural healthcare supply chain in India using system dynamics. Proc. Eng. **97**, 2204–2212 (2014)
43. Kussainov, A.: Use of system dynamics and simulation in modeling and analysis of vaccine supply chain management. Inf. Technol., Manag. Soc. **8**(1), 32–37 (2015)
44. Sterman, J.D.: Modeling managerial behavior: misperceptions of feedback in a dynamic decision making experiment. Manage. Sci. **35**(3), 321–339 (1989)
45. Jouzdani, J., Shirouyehzad, H.: Fight against COVID-19: what can be done in the case of Iran? J. Appl. Res. Ind. Eng. **7**(1), 1–12 (2020)
46. Yang, X., Yu, Y., Xu, J., Shu, H., Liu, H., Wu, Y., Zhang, L., Yu, Z., Fang, M., Yu, T.: Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. Lancet Respir. Med. **8**(5), 475–481 (2020)
47. Bhatraju, P.K., Ghassemieh, B.J., Nichols, M., Kim, R., Jerome, K.R., Nalla, A.K., Greninger, A.L., Pipavath, S., Wurfel, M.M., Evans, L.: Covid-19 in critically ill patients in the Seattle region—case series. N. Engl. J. Med. **382**(21), 2012–2022 (2020)
48. Senge, P.M., Forrester, J.W.: Tests for building confidence in system dynamics models. Syst. Dyn., TIMS Stud. Manag. Sci. **14**, 209–228 (1980)
49. Morshedi, M.A., Kashani, H.: A system dynamics model to evaluate the housing market response to vulnerability reduction promotion policies. Int. J. Disaster Risk Reduct. **44**, 101438 (2020)
50. Shreckengost, R.C.: HOW VALID ARE THEY? Paper presented at the Self-Report Methods of Estimating Drug Use: Meeting Current Challenges to Validity (1985)

COVID-19 Diagnosis with Artificial Intelligence

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Abstract Pandemics are epidemics that spread rapidly over countries or continents. They are large-scale outbreaks of contagious diseases that can significantly increase morbidity and mortality and cause substantial economic and social harm. If not properly controlled, the hospitals, physicians, and care staff become overloaded, driving the exponential growth of the infected population. Therefore, the early diagnosis of the infected would help to break the transmission chain. Artificial intelligence (AI) methods and deep networks have proven their outstanding performance in many fields. In this chapter, we discuss the potential use-cases of AI in controlling the COVID-19 pandemic. We introduce general concepts of AI in the diagnosis and screening of COVID-19. We also highlight common problems and pitfalls in developing AI methods with experiments on actual data. We ascertain the certainty of interpretable AI models for a trustful diagnosis. We study the state-of-the-art techniques in the diagnosis of COVID-19. We examine some of the experiences in controlling the COVID-19 pandemic and discuss why AI was not used to its full potential in the COVID-19 pandemic. Finally, we propose some future works to prevent the discussed problems in future pandemics.

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Acronyms

AI	artificial intelligence
ML	machine learning
NLP	natural language processing
KNN	K-nearest neighbors
SVM	support vector machine
AUC	area under the curve
CT	computed tomography
MRI	magnetic resonance imaging
CXR	chest X-ray
API	application programming interface
PCR	polymerase chain reaction
SOTA	state of the art
PET	positron emission tomography
NIH	National Institutes of Health
WHO	World Health Organization
HMS	health monitoring system
PHO	Ontario Health Services
RSNA	Radiological Society of North America
GPS	global positioning system

1 Introduction

Pandemics are epidemics that spread rapidly over the globe. If not properly controlled, the hospitals, physicians, and healthcare staff become overloaded, which results in substantial morbidity and mortality and causes significant economic and social harm. During the pandemics such as COVID-19, patients flock to hospitals at any time of the day, and many others check in with the mildest symptoms. Healthcare workers need to be present at all times, and severe fatigue can affect their performance. As a gold standard, the Polymerase Chain Reaction (PCR) test is used to confirm the presence of COVID-19. However, PCR is time-consuming and has high false-negative rates. Therefore, in some medical centers, they have been replaced by Computerized Tomography (CT)-scan imaging (A non-invasive imaging technique that gives detailed three-dimensional images from the body). CT-scan diagnosis by a specialized radiologist is faster, contains more details about pneumonia, and can provide a quantitative measurement of the severity of infection [1]. However, experts are not always available, and pandemics can exacerbate these conditions.

In these situations, accurate and rapid diagnosis of the disease effectively prevents the outbreak of a pandemic. However, factors such as the increasing workload of physicians and lack of expert radiologists in a pandemic make screening and identifying suspicious patients difficult and slow [2]. However, due to the high transmission rate of the COVID-19 pandemic, rapid diagnosis of the disease is necessary. Artificial intelligence (AI) systems can pressure off the medical centers by assisting physicians in speeding up the diagnosis and treatment procedures. They can also help the physicians to make early predictions and efficiently manage the available resources to control the spread of disease.

Artificial Intelligence is the ability of a computer to perform tasks commonly associated with intelligent beings [3]. The core of an AI system is its knowledge processing unit. The system uses this unit to acquire knowledge and perform specific tasks [4]. In Machine learning (ML), an important domain in AI, rules are learned from data and used to make accurate decisions. Computers have advantages over humans that make them more suitable to perform specific tasks. They can perform calculations much faster, have more memory to remember what is essential, and are perpetually available. They never get tired, never change modes, and no internal state affects their decision-making process. For example, the COVID-19 diagnosis of CT-scan takes up to 15 minutes for a radiologist, while it takes only a few seconds for an AI-based method [5]. Another challenge in the COVID-19 pandemic is distinguishing between COVID-19 pneumonia and other bacterial and non-COVID-19 viral pneumonia types. AI can help inexperienced physicians improve their ability to correctly diagnose different types of infections [6]. In addition, compared with an experienced thoracic radiologist, AI can achieve higher sensitivity than radiologists at the early stages of the disease when the lack of human-visible abnormalities in CT-scan exist [7].

Resource planning is utilized in hospitals to determine whether the hospital can care for a patient's needs. However, planning becomes a challenge during a pandemic with overburdened hospitals and limited resources. The goal is to save as many lives as possible. In this case, they have no choice but to admit patients based on the severity of their condition and the possibility of their survival. Some patients do not need to be treated in the hospital. However, for others, hospitalization is essential. Therefore, determining the condition of each patient and predicting the required facilities becomes vital. AI can help with resource planning by learning complex patterns from symptoms, historical and clinical data. Currently, many AI models are being used to predict overall mortality for the next few months or even a year [8]. These methods use various information such as blood biomarkers, age, gender, and disease background of the patient to achieve accurate predictions [9].

During a pandemic, patients with varying degrees of severity are admitted to hospitals. However, not all of them need to be hospitalized. Moreover, hospitals can be a source of further infection, especially during a pandemic. For example, a study reported that 41% of 138 hospitalized patients with COVID-19 were infected after being admitted to a hospital [10]. The Health Monitoring System (HMS) allows patients to be monitored remotely. HMS is an advanced technology alternative to traditional patient and health management. It consists of a wearable wireless device, such as a wristband with a sensor, equipped with software for the specialist to access important medical information [11]. AI can help to monitor the patients on two levels. First, it can assess the condition more frequently than a physician to warn for irregularities. Second, it can also predict the patient's health condition to adopt the required precautions in the coming days.

Infectious diseases such as COVID-19 can spread from person to person by physical contact, droplets, saliva, or airborne [12]. Because of the rapid spread of the COVID-19 virus, it has a high rate of infection [13]. To prevent the outbreak of the disease, one approach is to implement a patient tracking system that immediately alerts individuals who have had recent contact with known cases of the disease during their viral period and prompt them to become isolated [14]. There are several ways to track down individuals who have had contact or interaction with patients affected by the COVID-19 virus. For example, by collecting data from Bluetooth-based tracking applications, GPS and social graphs, video surveillance, and CCTV cameras. Further information can be gathered from card transaction data, internet search and social media monitoring, text data, and network-based Application Programming Interfaces (APIs), which are intermediary programs that connect two other apps together. Automated systems powered by AI can be designed to analyze different data types and model a tracking system to control the pandemic [14–16]. However, challenges such as technical limitations, socioeconomic disparities, data privacy and security risks, and ethical issues still lie ahead [17, 18].

The following section describes the general concepts and guidelines for using an appropriate AI system to manage the COVID-19 pandemic, focusing on diagnostic and screening tasks. Then, we explain the potential problems and pitfalls of AI-based methods using experiments with actual data. In section three, we elaborate on the use of AI to facilitate various operations in a pandemic. In section four, we describe the State-Of-The-Art (SOTA) AI systems used to diagnose COVID-19. The last section discusses the obstacles to exploiting AI's full potential in the current COVID-19 pandemic and proposes future works to make AI more effective in a pandemic.

2 A Guideline to Develop AI Models for Diagnosis and Screening

Continuous screening and rapid diagnosis are two of the most frequent tasks in controlling a pandemic. The function of the standard COVID-19 screening test is to identify people with a higher risk of spreading the disease. Since asymptomatic transmission plays a significant role in a pandemic, using screening tests to classify patients becomes very important to reduce the outbreak of the disease. The purpose of these tests is not to confidently detect the virus but to identify the suspicious patients and isolate them to minimize the rate of infection. For example, chest X-ray (CXR) images are used for screening COVID-19 as they are widely available, inexpensive, fast, and contain helpful information for detecting COVID-19 infections [19–23]. In addition, some studies have shown that magnetic resonance imaging (MRI), PET imaging, and ultrasound can be used for diagnosis and screening. However, they are not usually used in clinical practice [24–30].

> On the other side, the goal of diagnostic tests is to detect the presence or absence of the virus in suspected patients of COVID-19. These tests may also identify the cause, location, and severity of the disease. If the screening result indicates the presence of the disease, diagnostic tests are required to confirm the infection. For instance, the PCR or CT-scan tests can confirm the presence of COVID-19 [1, 31–33].

There is a wide range of data sources for the detection of a virus. Usually, the easier, faster, and more available the data collection, the less accurate it becomes. Generally speaking, during the COVID-19 pandemic, the data range starts with mobile applications widely available and fast. It continues to PCR testing and CT-scan images, which are more accurate and less available. As mentioned above, screening tests require simple and rapid data collection, while diagnostic tests require more accurate data.

As described above, screening is conducted over a larger population. However, an expert is not available to assess the test in many cases. Although diagnosis is performed over a selected population, their number is still high in a pandemic, resulting in the extreme tiredness of the experts. In addition, there is a shortage of experts in some regions. AI can help in both tasks and assist the medical staff in making more accurate and rapid diagnoses. We provide a guideline for how an AI system can be trained for such tasks. We also describe the general concepts and the common problems and pitfalls in screening and diagnosis with several real-world examples [34–37].

2.1 Training, Testing, and Further Validation of AI Models

In the supervised learning approach for an ML model, everything starts from data. We do not embed the knowledge of how to decide or how to calculate in the model. Instead, we let the model learn its optimal configuration from the data. ML problems fall into three general categories of classification, regression, and clustering. There are a limited number of groups in classification problems, and the goal is to identify the group for each sample in the dataset. For example, in classification, the goal is to determine whether a person has a specific disease. In regression, each sample is associated with a continuous number, and the goal is to calculate that number. Calculating the percentage of infected lung regions in pulmonary diseases with pneumonia is an example of this category. In clustering, the samples do not have any assigned groups or numbers, and the goal is to group samples with similar patterns in the collected data. For example, clustering patients with different symptoms in an unknown disease can lead experts to the disease's possible stroke paths.

The procedure of deploying an AI model for a classification problem is depicted in Fig. 1. In a classification problem, the dataset consists of multiple samples from each

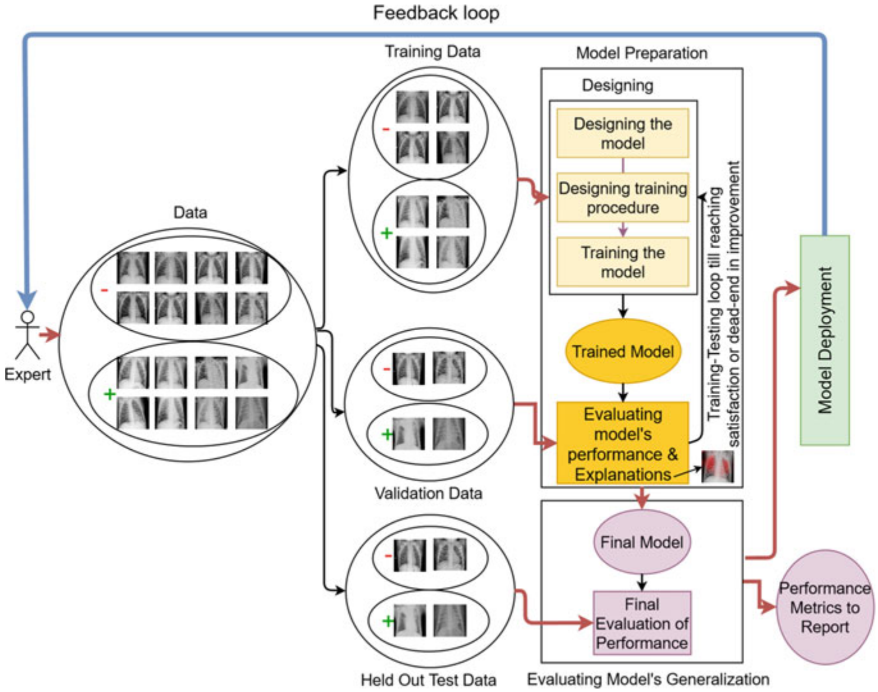

Fig. 1 The procedure of deploying an AI model for a classification problem

group or class. At first, the dataset is divided into three sets; training, validation, and test. Next, the training data is used to obtain the parameters of the model. A model may perform well on the training data but only learns the appearance of the samples as they are repeated in the training process. This phenomenon is called overfitting. To avoid over-fitting, multiple augmentations are applied to the input sample. For image data, rotation, geometric transformations, and changing brightness are examples of common augmentations. Finally, the trained model is evaluated on the validation data to make sure it has learned the general properties of the data. In addition to evaluation metrics, interpretations of the network may also be used as an extra check to validate the reasons behind the model's decisions.

Different architectures and training procedures lead to various performances of the model on training and validation sets. The one with the best performance on validation data is selected as the final model among the trained models. In evaluating the performance on validation data, redesigning, and retraining the model, the validation set is observed multiple times. Therefore, the model's performance on the validation set cannot be a fair metric for the model's generalizability. Therefore, a test set is held out to evaluate the model's performance on completely unseen data.

In some cases, models are designed to fit specific data appearances. As a result, they may fail on other samples, e.g., samples of another imaging device, harming the model's generalizability. Therefore, collecting the test data from sources other than the training and validation data can improve the model's generalizability. At the final step, the model is deployed and tested by an expert. The feedbacks are collected and returned to the model to make it optimal.

2.2 Data Gathering and Soundness

As mentioned above, an ML algorithm learns the model from data. Therefore, it is essential to have a diverse dataset to enforce the model learn different observations. Otherwise, it is limited to what it has seen and may perform poorly for other datasets. For example, it is crucial to consider patients with different stages of the disease for diagnosis, including healthy people in the dataset. If the training dataset only consists of the severe stage of the disease, it may fail to detect the early stages of the disease.

Another important point is to ensure the labels are correctly assigned to the dataset samples because the model learns from those labeled samples. If an expert labels the samples, the model will become biased towards the expert's opinion. Having confirmation from experts, using laboratory tests, and post-data-gathering samples' observations ensure correctness and make the model more robust. Another problem induced by the inexactness of the labels is the trainability of the model. When there are many mistakes in labeling, the model fails to train well. Therefore, we designed an experiment to investigate the effect of inappropriate data labeling on AI models. We selected two groups of data, one from NIH's chest-X-ray dataset [38] and the other from RSNA's chest-X-ray dataset [39]. The NIH's dataset contains 112120 images that are labeled using natural language analysis on the radiological reports. Therefore, they may be inexact. On the other hand, RSNA's dataset is a subset of NIH's dataset that at least two experts annotate to make it more trusted. Therefore, we gathered "No Finding" and "Pneumonia" samples of NIH's dataset for the first group, including 45449 negative and 696 positive samples. We collected "Healthy" and "Pneumonia" samples of RSNA's dataset for the second group, including 8851 negative and 9555 positive samples.

To eliminate the effect of unequal group sizes, some of the negative samples of NIH and some of the positive samples of RSNA were randomly discarded. As a result, 8851 negative samples and 696 positive samples remained for both groups. Next, 80% of the datasets Were selected as the training set and the rest as the validation set. Finally, two well-known models, Inception V3 [40] and ResNet18 [41], were trained with the Adam optimizer [42]. We utilized transfer learning and initialized the weights using the trained models available in the Torchvision package [43]. For both models, we first tuned the last fully connected layer and then one block before that. To avoid the effect of imbalanced classes, batches of size 32 containing 16 positives and 16 negative samples were used for training. Data augmentation techniques such as random brightness, cropping and resizing, rotating, and shearing was used to expand the dataset for generalization.

The epoch acquiring the best average sensitivity and specificity on the validation data was selected for all the models. The fine-tuning was done in the second stage

Table 1 The effects of inappropriate data labeling. Sens, sensitivity; spec, specificity

Train set	NIH (inappropriate labeling)		RSNA (appropriate labeling)	
Stage	Validation	Test	Validation	Test
Metric	Sens Spec Avg	Sens Spec Avg	Sens Spec Avg	Sens Spec Avg
Inception v3	56.67 86.45 71.56	59.12 77.79 **68.46**	88.33 95.23 91.78	78.55 80.41 **79.48**
ResNet 18	66.67 77.92 72.29	49.45 64.62 **57.04**	87.22 96.24 91.73	54.38 94.82 **74.6**

and continued until the model achieved more than 98% sensitivity and specificity for the training data. The epoch with the best performance on validation data was selected as the final model. We tested the models with the dataset of COVID-19 radiography database [44], Chest X-Ray Pneumonia [45], and Kaggle VinBigData [46] to evaluate their generalizability. The results for validation and test datasets are presented in Table 1.

As results show, both models trained on the NIH dataset fail to achieve high-performance metrics as the models trained on RSNA with the validation set. This proves that in datasets of equal size, certainty on labels helps exceedingly in training the model. Apart from the low sensitivity achieved on the test data due to the shortage of positive samples in the selected groups, the models trained with RSNA samples have achieved higher performance metrics for the test data.

2.3 Data Diversity, the Problem of Batch Effect and Generalization

In the COVID-19 pandemic, many published papers have used small datasets and reported high evaluation results. However, in most cases, the samples related to different classes were collected from other sources. Therefore, these models are susceptible to bias toward the appearance of samples for each dataset instead of learning to solve a general problem. As a result, the models lack generalization and may fail when applied to unseen data. This problem is not specific to small datasets, and large datasets may also have the same issue. For example, suppose the test set was gathered from the same training and validation datasets. In that case, the problem would not be identified in the final evaluation stage, and a problematic model will be deployed.

We designed an experiment to show the destructive effect of bias and batch effect in an intense investigation. We selected two groups of data from Kaggle's chest Xray Pneumonia and Kaggle's RSNA challenges. Both challenges were intended for detecting pneumonia from chest X-ray images. We selected pneumonia samples from the RSNA dataset and healthy samples from the chest-X-ray Pneumonia dataset for the first group, including 9555 positive and 1583 negative samples. We selected the same amount of positive and negative samples from both datasets for the second group. We selected 80% of the datasets as the training set and 10% as the validation

Table 2 The problem of batch effect and generalization caused by a biased dataset

Dataset	Group 1—biased dataset		Group 2—unbiased dataset	
Stages	Validation	Test	Validation	Test
Metrics	Sens Spec Avg	Sens Spec Avg	Sens Spec Avg	Sens Spec Avg
Inception v3	99.19 100 99.59	24.62 5.08 **14.85**	93.14 94.81 93.98	97.95 89.28 **93.61**
ResNet 18	99.65 100 99.82	16.15 2.60 **9.37**	94.88 94.07 94.48	98.21 92.33 **95.27**

set. 10% of each primary dataset was put aside as the shared test dataset. We eliminated the positive samples related to the RSNA dataset and the negative samples of the chest X-ray Pneumonia from the test set to bold the differences. The training and model selection was performed similarly to the scheme mentioned in Sect. 2.2. The evaluation results of the models are presented in Table 2. As the table shows, the models trained on the first group have reached high sensitivities and specificities on the validation set, which has the same bias as the training data. One may think the models perform even better than the second group considering the performance metrics of the validation sets. However, as the evaluation of test data with inverse bias shows, the models of the first group have become entirely biased toward the appearances of the samples for each dataset. In contrast, the evaluation metrics of the second group on the test set are similar to the validation set results.

2.4 Interpreting the Black-Box Deep AI Models

Deep neural networks have shown excellent performances, achieving high accuracies in many domains, even better than human experts. However, most of these models are black-boxes, meaning the internal decision-making mechanism of the network at the intermediate layers is not known. Therefore, their high accuracy is not sufficient to build trust toward them. Consequently, they may have performed well due to wrong reasons that are irrelevant to the domain-specific concerns [47]. In recent years, researchers have focused on interpreting the black-box models. Interpreting means explaining the reasons behind the decision of a model in a human-understandable way [48]. These interpretations help identify the bias in the model's decisions, make sure the model has been fair, monitor the model performance based on the reasons behind the decisions, and learn unknown domains from the model [47].

To show the trace of bias in the models, we interpreted the decisions of the above ResNet18 model using Guided Grad-CAM [49]. The interpretations will show which parts of the images were considered by each model to make a decision. Figure 2 presents the interpretation results of the models on seven random pneumonia samples from the test dataset. As the figure shows, the model trained on the biased dataset pays more attention to the outside regions of the lung, while the other model focuses on lung infections. It shows that the model trained on the biased dataset has learned

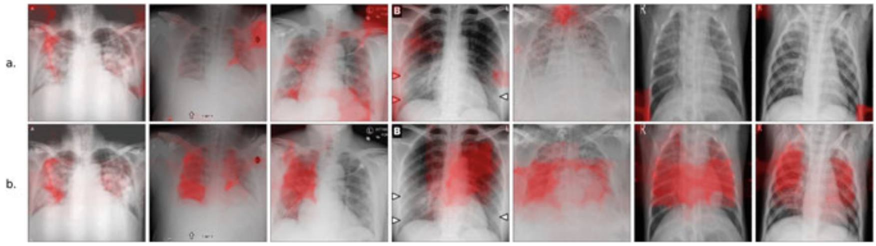

Fig. 2 Comparing interpretation results on ResNet18 using Guided Grad-CAM, trained on **a** the biased, and **b** the unbiased datasets

the apparent differences between the two datasets as the distinguishing feature of the patient and healthy images, instead of learning the patterns of pneumonia.

3 State-Of-The-Art AI Technologies for COVID-19 Diagnosis

Physicians in many countries have adopted imaging techniques and test kits to obtain more accurate diagnosis results of COVID-19 and determine the severity of the disease for each patient. CT-scan imaging is more accurate and sensitive among other imaging techniques, and many researchers have worked on the automatic diagnosis of COVID-19 using CT-scan images. Some have also focused on estimating the severity metrics for the patients. In addition to detecting infected from healthy individuals, some have also aimed to solve the more difficult problem of distinguishing COVID-19 from other lung diseases such as community-acquired pneumonia. Unfortunately, a fair comparison between published results is impossible due to the lack of benchmark datasets. Therefore, most studies applied similar steps with a limited number of choices on different datasets. Consequently, we discuss the existing challenges and the general methods used by other studies to overcome these challenges in the case of COVID-19 diagnosis. The details and performance measures for the selected studies are given in Table 3.

Diagnosis with CT-scan images is not a straightforward problem. It includes many challenges, and researchers have used different methods to overcome these challenges. For example, CT-Scan samples may have a different number of images, from 30 to 800, depending on the thickness of the cuts. This poses a significant challenge to the learning process. Some researchers have focused on high-resolution samples to keep the sensitivity and accuracy high [50]. In contrast, the others have trained their model on large cohorts with different thicknesses to have a more generalized model [6, 51, 52].

The COVID-19 CT-scans datasets usually have labeled samples. This is because carefully annotating images associated with infection and images with disease features is time-consuming, while radiologists focus on their primary tasks during the

Table 3 Details and performance metrics of the SOTA studies in diagnosing COVID-19

References	Classification groups	Training data	Test data	Evaluation metrics on test data
[50]	COVID-19 vs CAP vs Non-pneumonia	1165 COVID-19 1560 CAP 1193 Non-pneumonia [6 centers]	127 COVID-19 175 CAP 132 Non-pneumonia	Sensitivities for each group: COVID-19: 90% CAP: 87% Non-pneumonia: 94% AUC for COVID-19: 0.96
[6]	COVID-19 vs. nonviral CAP vs Influenza A/B vs Non-pneumonia	1294 COVID-19 666 nonviral CAP 70 Influenza A/B 1233 Non-pneumonia [3 centers + 2 public datasets]	1235 COVID-19 668 nonviral CAP 62 Influenza A/B 1234 Non-pneumonia [3 centers + 2 public datasets] 2113 COVID-19 1528 CAP 1333 Non-pneumonia [2 public holdout datasets]	Sensitivities for each group: COVID-19: 87.04% CAP: 96.88% Influenza A/B: 83.08% Non-pneumonia: 93.44% 2 Other public datasets: COVID-19: 84.66% CAP: 88.24% Non-pneumonia: 81.91%
[53]	COVID-19 vs others	703 COVID-19 684 non-COVID-19 [more than 7 centers]	326 COVID-19 1011 non-COVID-19 [more than 7 centers]	Sensitivity: 84.0% Specificity: 93.0% AUC: 94.9%
[54]	COVID-19 vs Influenza A vs Healthy	189 COVID-19 194 Influenza A 145 Healthy (3 centers)	30 COVID-19 30 Influenza A 30 Healthy	Sensitivities of each group: COVID-19: 86.67% Influenza: 83.33% Healthy: 90.0%
[51, 57]	COVID-19 vs CAP vs Normal	[Inexact numbers] 3000 COVID-19 750 CAP 500 Normal [from 15 countries]	[Inexact numbers] 250 COVID-19 200 CAP 100 Normal [from 15 countries]	Sensitivities for each group: [slice-based evaluation] COVID-19: 96.2% CAP: 98.2% Normal: 99.0%

(continued)

Table 3 (continued)

References	Classification groups	Training data	Test data	Evaluation metrics on test data
[52]	COVID-19 and non-COVID patients vs. Healthy COVID-19 vs non-COVID patients	1995 COVID-19 513 non-COVID-19 patients 517 Healthy [from 6 centers]	222 COVID-19 57 non-COVID-19 patients 519 Healthy [from 6 centers] 1435 COVID-19 [from 6 other hospitals]	Sensitivities: Diseased: 97.25% Healthy: 87.50% COVID vs Other diseases: COVID-19: 98.15% Other: 81.03% [for unseen centers] Diseased: 95.80% COVID-19 vs others: 95.73%

pandemic. Having many images per sample and being trained only on the samples' labels is like looking for a needle in a haystack for a model that does not know about the disease. When we train a model to distinguish between groups of samples, the model tries to learn the groups' differences. Searching in a large sample makes the training process harder and slower. Moreover, a sample of almost 200 images can fill the memory of a common GPU with 12 GB of RAM. Therefore the training becomes even more difficult.

Integrating human knowledge about the disease to the method, architecture of the model, and training process can significantly reduce the training challenges. It can also help the model learn relevant differences, which helps distinguish the groups of samples. For example, since we know COVID-19 affects the lungs, it would be logical to search for the marks of the disease in the lung areas of CT-scan images. Many researchers have adopted this knowledge in a pre-processing step. Some have used image processing techniques such as automatic thresholding to separate the lung areas from images. Some have trained a network over their own annotated private dataset to detect the lungs [6, 50–54]. Therefore, the rest of the images are eliminated except for the lungs, and the model skips the irrelevant areas during the training process.

Researchers have tried to ease the challenge of training with different methods. Some have adopted a fully supervised approach by providing slice-based labels and training their model to classify the slices rather than the whole image [51]. While being very helpful in training the model, this solution suffers from being biased to the error of the annotator. Even if the error were reduced by aggregating the annotations from multiple radiologists, there would still be a problem with the lack of human-detectable signs. This means the model will at most be able to distinguish what radiologists can distinguish. In practice, we have many unlabeled samples and only a limited number of labeled samples. Therefore, Some researchers have adopted semi-fully supervised methods for the training process. This is possible by adopting a two termed loss function; one for the sample-level prediction and the other for the slice-level prediction. The first term is calculated over all the samples of the training batch, but the second term only focuses on samples with specific slice labels. Here the sample-level loss considers the slices with a lack of human observable marks. Thus, the slices with a negative label belonging to a positive sample should not be included as healthy slices in the training process for the annotated samples. Finally, many researchers have trained their models merely based on the sample-level labels and achieved notable results [6, 50, 52, 53].

COVID-19 is detected mainly by ground-glass opacity infections in the peripheral of the lung. Some researchers [52, 55] have developed their method based on this knowledge. First, they utilize the existing models and tools for pulmonary lesion detection that specify the regions of the lesions [56]. In the next step, they use deep learning models to classify the type of lesions and aggregate the results of the lesions to decide for the whole sample. Unfortunately, these methods may also miss the samples with the lack of human-detectable marks.

Diagnosing COVID-19 from CT-scan images is inherently a 3D problem. This is because the images of the CT-scan are cuts through another dimension, named depth. Some researchers have treated CT-scan images as 3D data, extended the 2D models to work with 3D data, and used the sample-level labels to train the model [6, 53, 54]. These models utilize 3D convolutional kernels and demand much more GPU memory than the 2D models during the training, and have more extensive computations in the evaluation phase. In addition, they are more sensitive to the thicknesses of the slices as convolutional networks are not invariant to different scales. Others have worked merely on 2D models and classified slices rather than the whole samples [51]. Other researchers have just aggregated the features extracted from the slices before making the final decision using a pooling layer [50] or an LSTM network [6]. However, they miss the information that the peripheral slices can add to each slice. Other researchers have adopted a hybrid 2D-3D model to have advantages of both schemes. They have used 2D models to extract information from individual slices and added the peripheral slices as extra channels to the input slices. Another problem with the 2D and the hybrid methods is their requirement for slice-level labels in the training phase. Some have overcome this problem by aggregating the features extracted from slices before the decision-making section of the network. To solve the problem with GPU's memory, they have subsampled uniformly from different parts of the sequence of images for each CT-scan. It is more probable to capture the disease-related marks in at least one of the chosen slices in subsampling. Some others have used a weakly supervised approach to dynamically guess the slices related to the disease in each round of training [52]. Moreover, for the 2D and hybrid models, an additional post-processing step must be considered to reduce the false positives. Many have used Markov models to extract more reasonable probabilities for slices based on the probabilities of the peripheral slices.

To train the models for detecting infections and diagnosing COVID-19, pixel-level labels are required. This takes even more effort from radiologists for annotations. Researchers have used fully supervised, semi-supervised, and weakly supervised schemes for training the model based on slices of CT-scan images. There have also been other weakly supervised schemes that use the interpretations of the model to perform sample-level or slice-level predictions for finding the input areas that affect the output. They use these areas as ground truth and train the infection detection model by utilizing them [below]. In detecting infection, fully supervised and semi-supervised methods can lead to more accurate results. In contrast, the weakly supervised methods would only detect approximate zones due to many pixels and the inexact labels used in training.

4 AI and Pandemic

This section addresses other areas where AI can help speed up processes in managing the pandemic.

4.1 AI for Status Prediction

Two different approaches have been taken to study COVID-19 mortality; predicting large-scale mortality and predicting the death of each individual according to its condition. The first approach is commonly used to predict mortality in a city or country. It uses the distribution of mortality rates in recent days and weeks to predict the near future. To achieve higher accuracy, parameters such as hospital facilities, human mobility, non-pharmaceutical interventions, demographics, historical air quality, and econometrics in the area can also be considered [58].

The second approach predicts the probability of death for each individual. It uses different models like Neural Networks, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and Decision Tree to obtain the highest accuracy. For example, in our study, the neural network model achieved 89.98% accuracy in predicting the mortality of COVID-19 patients.

In addition, in [59] they trained an AI model on a large dataset of hospitals in Ontario, with nearly 70 thousand patients. Data were collected from the Ontario Health Services (PHO) and Canada Health Services (PHAC) datasets. The model achieved an Area Under the Curve (AUC) of 90% for PHO and 93.5% for PHAC datasets.

4.2 Utilization of AI in Vaccine Discovery

To combat the COVID-19 pandemic, vaccination is the most effective strategy. Most SARS–CoV-2 vaccines in advanced clinical trials are based on modern vaccine approaches that rely on introducing the specific parts of the virus or their genes into the body to generate a targeted immune response. Thus, current methods have shifted away from live-attenuated and inactivated whole-pathogen vaccines to purified antigens and epitopes.

Vaccine development is complex and often requires extensive, time-consuming, and resource-intensive studies to determine efficacy and potential side effects. AI can help speed up the lengthy and costly process of vaccine development.

The vaccine design process has been revolutionized by reverse vaccinology, which focuses on finding potential vaccine candidates by analyzing pathogens' protein-coding genome (proteome). The SARS–CoV-2 consists of four structural proteins, E (envelope), M (membrane), N (nucleocapsid), and S (spike), as well as several non-structural proteins. The AI approaches can facilitate antigen selection, epitope prediction, immune response modeling, and affinity with human leukocyte antigen alleles in the vicinity of COVID-19 to select the best possible ones. Numerous epitope prediction studies focused on this protein since the S protein is involved in viral entry and provokes an immune response. BNT162b2, mRNA-1273, and AZD1222 are three recently approved vaccines against SARS–CoV-2, all of which use the S protein. Thus, AI approaches can identify specific epitopes from a significant number of potential SARS SARS–CoV-2 peptides capable of inducing a robust and protective immune response.

Another critical problem that could be solved by an AI-based method in predicting the immunogenicity of the developed vaccine. In search for SARS–CoV-2 proteins associated with optimal immune response, computational biology can identify gene coding proteins associated with COVID-19 severity. In addition, a cellular immune response network can be constructed using host-virus and virus-host interaction data.

One of the significant challenges in vaccine development lies in the mutations of SARS–CoV-2 strains. Therefore, there is a need to test whether a selected epitope is conserved across mutations and multiple populations for vaccine development. Despite the development of several machine learning-based classifiers for allergenicity and toxicology, there is currently no method for predicting the toxicity of all vaccine components in combination, which computational network analysis could achieve [60]. Furthermore, breeding SARS–CoV-2 variants resistant to the approved vaccines is not impossible. Therefore, more robust and precise AI-in-silico approaches should be developed to a better vaccine against the new variants of the virus.

4.3 AI in Controlling the Pandemic

COVID-19, as a global health crisis, forced the health care providers to seek new technologies to monitor and control the spread of the pandemic. The extraordinary amount of data derived from public health surveillance, real-time epidemic outbreak monitoring, trend forecasting, regular situation briefings, and medical records must be managed to control and anticipate new diseases.

AI-based methods can track the spread of the virus in real-time, plan public health interventions and monitor their effectiveness. Indeed, the flexibility, rapid analysis

Table 4 Possible applications of artificial intelligence and big data for the management of the COVID-19 outbreak

Time scale	Possible application	Example
Short-term (weeks)	Rapid identification of an ongoing outbreak	AI can facilitate real-time epidemiological data collection, risk-assessment, decision-making processes, and design/implementation of public health interventions
	Diagnosis and prognosis of COVID-19 cases	Recognition of specific diagnostic and prognostic features
Medium-term (months)	Identification of a potential therapeutic option	Identify already existing drugs/discovering new molecules
Long-term (decades)	Enhancing cities and favoring the development of healthy, intelligent, resilient cities	Design newly standardized protocols for sharing data and information during emergencies

and identification of patterns, ability to adapt based on a new understanding of the disease process, self-improvement as new data become available, and lack of human bias in the analysis make AI a promising new tool for pandemic management. Table 4 indicates some possible applications of AI in the control and management of the COVID-19 pandemic.

Information obtained from patient tracking plays a vital role for general public health governance in designing, planning, and organizing to cope with the pandemic [15]. Researchers in [18] have listed 36 countries that have successfully implemented mobile app patient tracking systems. There are several ways to achieve this goal as follows.

4.3.1 Patient Tracking Using Mobile Apps

A successful example is the QR-code-based screening app used in Hubei, China, to monitor people's movement. A similar approach has been used in Taiwan to track high-risk individuals based on their travel history to affected areas [61, 62]. Tracking information from Internet-based searches can also help to predict future outbreaks [61]. For example, using WeChat text data in the context of COVID-19 was another successful approach to predicting disease outbreaks in China [63]. In addition, by searching for "fever" and "cough" in Google Trends, the researchers discovered that these words had a significant association with the COVID-19 outbreak and subsequent hospitalizations or deaths [22].

4.3.2 Patient Tracking Using Video Surveillance

Using video surveillance to detect proximity and social distance has advantages over other approaches such as Bluetooth or GPS technologies. However, the methods mentioned above lead to a high rate of false positives due to their low spatial resolution. Other studies show deep-learning approaches for analyzing CCTV cameras in the workplace to monitor workers' activities and detect violations [64, 65]. In another study, a facial touch detection system (that detects when someone unconsciously touches their face) was also developed to ensure security and collect more data that can be used in related applications [66].

4.3.3 Patient Tracking Using Natural Language Processing (NLP)

An important application of machine learning in patient tracking is determining public opinion and society's perception of social distancing [67]. For example, the results of a text classification study showed that public opinion plays a vital role in guiding relevant decisions (sentiment analysis to ensure that they have been well taught) [14].

There are also challenges with current mobile apps [14]. For example, technical limitations include a lack of highly skilled developers and companies developing and deploying the tracking system. Different countries like the US, UK, and Australia have come to other solutions to overcome this problem [18].

Unfortunately, there is not enough quantitative information about the contact tracing apps used in the above countries to compare their performance and other features comprehensively.

However, in [68], the authors mentioned a COVID-19 Tracing App Scale (COVIDTAS) framework to compare these apps. COVIDTAS was adopted from a framework in [69] and developed based on features such as usability, technology, privacy, tracking effectiveness, and factors reflecting user experience and sentiment.

4.4 Wearable Sensors Application in COVID-19 Pandemic

Other trending approaches that are progressively developing are COVID-19 wearable devices. Despite the classic and conventional techniques used in clinical settings like PCR tests or imaging modalities, these approaches have continuous access to health records of potential COVID-19 subjects all day long. At present, devices like smartwatches or wristbands are recording health data used for screening purposes. Moreover, wearable devices like smart lenses, smart on-teeth sensors, smart masks, and smart biosensors are gaining more attention. However, possible precautions of these technologies, such as data privacy, must be considered [70, 71].

More recently, observational studies on wearable biosensors for remote monitoring of COVID-19 subjects by AI algorithms have revealed promising performance in detecting COVID-19 patients. Un and his colleagues designed their observational study to show the potentials of wearable biosensors and AI in clinical monitoring. They illustrated that wearable biosensors with AI reached a high correlation with manual procedures in predicting clinical worsening events, as well as prolonged hospitalization [72].

Additionally, there are other related works in literature, including newly-developed wearable devices and state-of-the-art AI algorithms that can predict the potential outcomes of disease. As another example, a wireless skin-interfaced device attaching to the suprasternal notch designed by FitBit can sense multiple features like body movement, heart rate, respiratory-related signals, and other signs and symptoms like body temperature and cough. Therefore, by an ongoing fusion of these features by utilizing AI techniques, one can classify or predict diseases (e.g., being COVID-19 or not) more accurately [73].

5 Future Directions

5.1 The COVID-19 Pandemic Experience

Since the COVID-19 outbreak in late 2019, the disease has become a potential threat to global health. Facing a pandemic is cross-sectoral. These sectors, including economy, social, cultural, environmental, and political, are collectively called social determinants of health.

In a 2000 report, the World Health Organization (WHO) outlined the primary role of health systems in achieving their goals through a set of six fundamental building blocks, including service delivery, health workforce, health information systems, medical products, vaccines and technology, health financing, and governance. Information and AI technologies that serve these six principles can increase the resilience of health systems.

The strategy of countries on health systems plays a crucial role in controlling pandemics. COVID-19 pandemic showed a fundamental weakness in international organizations and governments to face a pandemic. For example, WHO made basic mistakes in managing the COVID-19 pandemic. Without sufficient information, it declared the virus is non-communicable and considered the use of the mask unnecessary for a long time. A year and a half after the pandemic, COVAX vaccine distribution policies cannot provide comprehensive vaccination plans. In the COVID-19 pandemic, medical advances in specialized fields did not help significantly. Unfortunately, at the beginning of this crisis, due to incorrect policy-making, the influx of hospitals and emergency rooms caused the spread of the virus and increased mortality.

Since it is time-consuming to find effective vaccines and treatments at the beginning of a pandemic, the most important global action is identifying and tracking patients and implementing smart distancing between citizens. The experience and evidence of successful countries in the field of COVID-19 pandemic management in the world have shown that most of the successful management activities are based on the correct and timely application of AI solutions. The first step in managing the information of any epidemic is to identify and record the information of the target population. Accurate identification and registration of patients in different disease states are possible through the following:

1. Identifying the exact number of cases and the actual geographical prevalence,
2. Preparation of contact tracking map of infected people and carriers and the possibility of predicting the future pattern of outbreaks,
3. Ability to control the movement of the population for the best type of social/physical distancing policy, and
4. Anticipating the needs and resources of care and treatment, focusing on efficient distribution of resources.

The following steps are suggested for implementing a control and management system:

1. Implementing a national pandemic web-based system,
2. Identifying the status of each individual; without symptoms, suspicious symptoms, definitive infected, and convalescence categories,
3. Launching a status inquiry system
4. Requiring citizens to carry pandemic IDs,
5. Electronic screening process through registering geographical position and an AI algorithm to compute the risk of being infected by being near the patients and suspected people,
6. Tracking patients through their phones and GPS,
7. Establishing an AI-based face tracking system for patients to prevent them from entering crowded areas,
8. Developing AI-based screening systems that recognized patients through their temperature or other characteristics,
9. Developing AI-based chatbots, and
10. Preparing a telemedicine system to checkup patients in remote locations.

We should adopt new data collection and analysis strategies using emerging technologies. For example, the Internet of Things (IoT) refers to the interconnected network of physical objects such as sensors, health measuring devices, intelligent sensors, home appliances, automotive devices, etc. IoT enables objects to sense, process, and communicate with each other and automatically interact with people and provide intelligent service to users. The IoT platforms can also be used over cloud computing platforms to provide systematic and intelligent prevention and control of COVID-19, which includes five steps: symptom detection, quarantine monitoring, disease contact detection, and social distancing, disease prognosis, and disease mutation tracking. If IoT, cloud, and AI are appropriately utilized, they can provide rapid and efficient healthcare services, especially in the perspective of COVID-19.

5.2 *Toward a Universal Crowd-Sourcing and Validating Framework for AI Models*

The AI methods have declared they can come in handy during the pandemics, although they have not shown a significant impact on the case of COVID-19 [74]. It was expected to have the AI methods emerge before the first COVID-19 peak in diagnosis and screening, which means scientists had few months to train sophisticated models. As mentioned before, having a large dataset with a wide variety is crucial to have generalizable models, while there was no public dataset in the said period for the COVID-19 pandemic. This led scientists to search the literature, hoping to find sufficient data, and another group searched among the care centers looking for data. However, sufficient positive cases cannot be located in one medical center in the emergence of a pandemic. Besides, there is numerous paperwork to satisfy the privacy of data, which takes even more time. In other words, much time would be spent on gathering the required data while it can be spent on designing and training a suitable model. These problems can be solved if there is a universal crowd-sourcing public dataset. There might be a lack of samples in a small area. However, there is undoubtedly enough data all over the world. Many people wish to donate their samples and contribute to making a universal public dataset to help scientists battling against the pandemic. This framework should have strict confirmation policies to ensure data validity and trustability. Other scientists like physicians and experts can also use this worldwide public dataset to study the disease comprehensively.

Unfortunately, the hotness of a pandemic causes a paper storm. In this situation, it is difficult and time-consuming to find state-of-the-art methods. The review papers ease this process by summarizing many studies. Nevertheless, there is a trade-off between the coverage of ideas and faster release. For example, in screening and diagnosing COVID-19 using medical images, there are more than 2000 papers, howbeit no review paper has covered more than a few methods. Another problem is that not many experts trust the papers in the arXiv, and it takes a long time to be published in a peer-reviewed journal or conference. These problems can be solved by having a universal public framework for sharing the data, papers, and results in a structured way. For example, in the case of diagnosing COVID-19, it could be a tabled data containing the date, the number of training samples, the number of test samples, classification groups, evaluation metrics on the private test set and also on public datasets, and some extra tags for the general methodologies like fully supervised, semi-supervised, weakly supervised, or unsupervised. Having tabled data like this could make searching the literature much easier and faster by utilizing AI-based filters and sorting tools. There are websites like https://paperswithcode.com/ that have aimed at a similar goal by introducing datasets and grouping the studies.

The experience of the COVID-19 pandemic showed that the potentials of AI methods did not widely explore to combat the pandemics. One reason is that people cannot easily trust the reported results. The results cannot be trusted unless one can trust the data and run the proposed trained model on the same data. Some organizations like Kaggle and Dream Challenge aim to solve global problems by challenging and validating the trained models with private test datasets. During a pandemic, the challenges can help to a great extend. Unfortunately, in the case of diagnosing COVID-19 using CT-scan images, there were no such challenges.

In conclusion, in the case of the COVID-19 pandemic, the absence of the proposed framework is evident. As a result, there was a delay in the emergence of sophisticated and trustable AI models, duplicate ideas on different private datasets, and no fair comparison. This happened while the studies could have been complementary and helped in the evolution of working solutions. The recent experience proved that the world had not been prepared for a pandemic. Efficient adoption of emerging technologies such as IoT, cloud, and AI can significantly help control and manage pandemics.

6 Conclusion

This chapter briefly introduced AI, its strong potentials, and its capability of making manual procedures faster and more accurate during pandemics. Considering its benefits, AI has a high potential to help in a pandemic where hospitals are overloaded, and health experts cannot respond on time. In recent years, AI models have shown outstanding performance in many health applications, especially during pandemics. Therefore, it is essential for the health staff who work with AI systems to know these models and how they operate. So, they neither overestimate nor underestimate them. We demonstrated how AI models are trained. We set up an experiment on actual data to show that models cannot be trained perfectly on any data. A more precisely labeled dataset can lead to much better training. We also showed that not every model that has reported high performance could be confidently trusted. Moreover, we set up an extreme experiment to show how a model can become biased to dataset-specific features, resulting in increased performance in the dataset and low performance in other general datasets. In this regard, we introduced the concept of explainability of AI models. We showed how explaining decisions could help understand and trust the model's findings, which can lead to understanding whether the model's decision on a single case is reliable and if the model is performing rationally in general or has become biased. When a model is biased to unrelated features, it will not behave as expected. In conclusion, the models need to be evaluated on a diverse set of test data representing the actual population's distribution so that the experts can trust the reported performance metrics.

We described the general applications of AI in pandemics and the corresponding SOTA studies. We focused more deeply on the role of AI models in diagnosis and screening as two essential requirements of breaking out a pandemic. Several methods of diagnosis and screening were used during the COVID-19 pandemic. As stated before, evaluating the models on large test sets can indicate their similar performance on the general population and, therefore, their applicability on large-scale situations. Consequently, we selected SOTA methods acquiring the desired quality. Due to the high overlap between the methods, we described the general methodologies and mentioned differences rather than the extensive description of those methods.

Finally, we demonstrated experiences during the COVID-19 pandemic that avoided exploiting the AI's full potentials. We stated the lack of valuable data and the tremendous required effort to gather datasets are the major delaying factors in delivering effective AI systems for the pandemic's peak time. We also described the effect of the so-called paper storm as another delaying factor. The literature review shows that most studies have reported similar performance on different private datasets. However, their performance on general datasets is unknown. Therefore, creating an open dataset could facilitate the delivery of effective AI solutions in a pandemic. We reported the lack of trust towards the reported performance metrics as a prohibitory reason for using AI models by experts. To solve the problems mentioned above, we proposed a unified framework for gathering data, effectively managing the paper storm, and trustfully evaluating the models that can be more effective in the next pandemic.

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References

1. Zhang, K., Liu, X., Shen, J., Li, Z., Sang, Y., Wu, X., Zha, Y., Liang, W., Wang, C., Wang, K., Ye, L., Gao, M., Zhou, Z., Li, L., Wang, J., Yang, Z., Cai, H., Xu, J., Yang, L., Cai, W., Xu, W., Wu, S., Zhang, W., Jiang, S., Zheng, L., Zhang, X., Wang, L., Lu, L., Li, J., Yin, H., Wang, W., Li, O., Zhang, C., Liang, L., Wu, T., Deng, R., Wei, K., Zhou, Y., Chen, T., Lau, J.Y.-N., Fok, M., He, J., Lin, T., Li, W., Wang, G.: Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography. Cell **181**(6), 1423–1433.e11 (2020). https://doi.org/10.1016/j.cell.2020.04.045
2. Huang, S., Yang, J., Fong, S., Zhao, Q.: Artificial intelligence in the diagnosis of COVID-19: challenges and perspectives. Int. J. Biol. Sci. **17**(6) 1581–1587 (2021). https://doi.org/10.7150/ijbs.58855
3. Copeland, B.J.: Artificial intelligence. In: Encyclopedia Britannica. Available via DIALOG., 2020. https://www.britannica.com/technology/artificial-intelligence. Accessed 21 April 2021
4. Kurfess, F.J.: Artificial intelligence. In: Encyclopedia of Physical Science and Technology, pp. 609–629. Elsevier (2003). https://doi.org/10.1016/b0-12-2274105/00027-2
5. McCall, B.: COVID-19 and artificial intelligence: protecting health-care workers and curbing the spread. Lancet Digit. Health **2**(4), e166–e167 (2020). https://doi.org/10.1016/s2589-7500(20)30054-6
6. Jin, C., Chen, W., Cao, Y., Xu, Z., Tan, Z., Zhang, X., Deng, L., Zheng, C., Zhou, J., Shi, H., Feng, J.: Development and evaluation of an artificial intelligence system for COVID-19 diagnosis. Nat. Commun. **11**(1) (2020). https://doi.org/10.1038/s41467-020-18685-1
7. Mei, X., Lee, H.-C., yue Diao, K., Huang, M., Lin, B., Liu, C., Xie, Z., Ma, Y., Robson, P.M., Chung, L., Bernheim, A., Mani, V., Calcagno, C., Li, K., Li, S., Shan, H., Lv, J., Zhao, T., Xia, J., Long, Q., Steinberger, S., Jacobi, A., Deyer, T., Luksza, M., Liu, F., Little, B.P., Fayad, Z.A., Yang, Y.: Artificial intelligence-enabled rapid diagnosis of patients with COVID-19. Nat. Med. **26**(8), 1224–1228 (2020). https://doi.org/10.1038/s41591-020-0931-3
8. Cerna, A.E.U., Jing, L., Good, C.W., vanMaanen, D.P., Raghunath, S., Suever, J.D., Nevius, C.D., Wehner, G.J., Hartzel, D.N., Leader, J.B., Alsaid, A., Patel, A.A., Kirchner, H.L., Pfeifer,

J.M., Carry, B.J., Pattichis, M.S., Haggerty, C.M., Fornwalt, B.K.: Deep-learning-assisted analysis of echocardiographic videos improves predictions of all-cause mortality. Nat. Biomed. Eng. **5**(6), 546–554 (2021). https://doi.org/10.1038/s41551-020-00667-9
9. Ko, H., Chung, H., Kang, W.S., Park, C., Kim, D.W., Kim, S.E., Chung, C.R., Ko, R.E., Lee, H., Seo, J.H., Choi, T.-Y., Jaimes, R., Kim, K.W., Lee, J.: An artificial intelligence model to predict the mortality of COVID-19 patients at hospital admission time using routine blood samples: Development and validation of an ensemble model. J. Med. Internet Res. **22**(12), e25442 (2020). https://doi.org/10.2196/25442
10. Wang, Y., Wang, Y., Chen, Y., Qin, Q.: Unique epidemiological and clinical features of the emerging 2019 novel coronavirus pneumonia (COVID-19) implicate special control 21 measures. J. Med. Virol. **92**(6), 568–576 (2020). https://doi.org/10.1002/jmv.25748
11. Gudadhe, A., Genani, G.: Wearable health monitoring systems. The Industrial Design Engineering Wiki (2021). http://wikid.io.tudelft.nl/WikID/index.php/Wearable_Health_Monitoring_Systems. Accessed 15 June 2021
12. W.W.H. Organization: Health topic, coronavirus disease overview (2020). https://www.who.int/health-topics/coronavirus#tab=tab_1. Accessed 29 May 2020
13. Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D., Fraser, C.: Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. Science **368**(6491), eabb6936 (2020). https://doi.org/10.1126/science.abb6936
14. Lalmuanawma, S., Hussain, J., Chhakchhuak, L.: Applications of machine learning and artificial intelligence for covid-19 (SARS-CoV-2) pandemic: a review. Chaos, Solitons Fractals **139**, 110059 (2020). https://doi.org/10.1016/j.chaos.2020.110059
15. Golinelli, D., Boetto, E., Carullo, G., Nuzzolese, A.G., Landini, M.P., Fantini, M.P.: Adoption of digital technologies in health care during the COVID-19 pandemic: Systematic review of early scientific literature. J. Med. Internet Res. **22**(11), e22280 (2020). https://doi.org/10.2196/22280
16. Saeedvand, S., Jafari, M., Aghdasi, H.S., Baltes, J., Rahmani, A.M.: Deep Learning: A Taxonomy of Modern Weapon to Combat Covid-19 Pandemic (2020)
17. Mbunge, E.: Integrating emerging technologies into COVID-19 contact tracing: Opportunities, challenges and pitfalls. Diabetes & Metab.Ic Syndr.: Clin. Res. Rev. **14**(6), 1631–1636 (2020). https://doi.org/10.1016/j.dsx.2020.08.029
18. Health, T.L.D.: Pandemic versus pandemonium: fighting on two fronts. Lancet Digit. Health **2**(6), e268 (2020). https://doi.org/10.1016/s2589-7500(20)30113-8
19. Das, D., Santosh, K.C., Pal, U.: Truncated inception net: COVID-19 outbreak screening using chest x-rays. Phys. Eng. Sci. Med. **43**(3), 915–925 (2020). https://doi.org/10.1007/s13246-020-00888-x
20. Basu, S., Mitra, S., Saha, N.: Deep learning for screening covid-19 using chest x-ray images. In: 2020 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 2521–2527. IEEE (2020)
21. Li, X., Li, C., Zhu, D.: Covid-mobilexpert: on-device covid-19 screening using snapshots of chest x-ray (2020). arXiv preprint arXiv:2004.03042
22. Punn, N.S., Sonbhadra, S.K., Agarwal, S., Rai, G.: Monitoring covid-19 social distancing with person detection and tracking via fine-tuned Yolo v3 and deepsort techniques (2020). arXiv preprint arXiv:2005.01385
23. Nayak, S.R., Nayak, D.R., Sinha, U., Arora, V., Pachori, R.B.: Application of deep learning techniques for detection of covid-19 cases using chest x-ray images: a comprehensive study. Biomed. Signal Process. Control **64**, 102365 (2021)
24. Fields, B.K., Demirjian, N.L., Dadgar, H., Gholamrezanezhad, A.: Imaging of covid-19: Ct, mri, and pet. In: Seminars in Nuclear Medicine. Elsevier (2020)
25. Yang, S., Zhang, Y., Shen, J., Dai, Y., Ling, Y., Lu, H., Zhang, R., Ding, X., Qi, H., Shi, Y., et al.: Clinical potential of ute-mri for assessing covid-19: patient-and lesion-based comparative analysis. J. Magn. Reson. Imaging **52**(2), 397–406 (2020)

26. Langenbach, M.C., Hokamp, N.G., Persigehl, T., Bratke, G.: Mri appearance of covid-19 infection. Diagn. Interv. Radiol. **26**(4), 377 (2020)
27. Abdelmohsen, M.A., Alkandari, B.M., Gupta, V.K., ElBeheiry, A.A.: Diagnostic value of abdominal sonography in confirmed covid-19 intensive care patients. Egypt. J. Radiol. Nucl. Med. **51**(1), 1–7 (2020)
28. Evans, K.D., Yang, Q., Liu, Y., Ye, R., Peng, C.: Sonography of the lungs: diagnosis and surveillance of patients with covid-19. J. Diagn. Med. Sonogr. **36**(4), 370–376 (2020)
29. Kaufman, A.E., Naidu, S., Ramachandran, S., Kaufman, D.S., Fayad, Z.A., Mani, V.: Review of radiographic findings in covid-19. World J. Radiol. **12**(8), 142 (2020)
30. Dong, D., Tang, Z., Wang, S., Hui, H., Gong, L., Lu, Y., Xue, Z., Liao, H., Chen, F., Yang, F., et al.: The role of imaging in the detection and management of covid-19: a review. IEEE Rev. Biomed. Eng. **14**, 16–29 (2020)
31. Al-Tawfiq, J.A., Memish, Z.A.: Diagnosis of sars-cov-2 infection based on ct scan vs rt-pcr: reflecting on experience from mers-cov. J. Hosp. Infect. **105**(2), 154–155 (2020)
32. Poortahmasebi, V., Zandi, M., Soltani, S., Jazayeri, S.M.: Clinical performance of rt-pcr and chest ct scan for covid-19 diagnosis; a systematic review. Adv. J. Emerg. Med. **4**(2s), e57–e57 (2020)
33. Gietema, H.A., Zelis, N., Nobel, J.M., Lambriks, L.J., Van Alphen, L.B., Oude Lashof, A.M., Wildberger, J.E., Nelissen, I.C., Stassen, P.M.: Ct in relation to Rt-PCR in diagnosing covid-19 in the Netherlands: a prospective study. PloS one **15**(7), e0235844 (2020)
34. Chowdhury, E., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M.A., Mahbub, Z.B., Islam, K.R., Khan, M.S., Iqbal, A., Al Emadi, N., et al., Can AI help in screening viral and covid-19 pneumonia? IEEE Access **8**, 132665–132676 (2020)
35. Castiglioni, I., Ippolito, D., Interlenghi, M., Monti, C.B., Salvatore, C., Schiaffino, S., Polidori, A., Gandola, D., Messa, C., Sardanelli, F.: Artificial intelligence applied on chest x-ray can aid in the diagnosis of covid-19 infection: a first experience from Lombardy, Italy. MedRxiv (2020)
36. Mangal, A., Kalia, S., Rajgopal, H., Rangarajan, K., Namboodiri, V., Banerjee, S., Arora, C.: Covidaid: Covid-19 detection using chest X-ray (2020). arXiv preprint arXiv:2004.09803
37. Borkowski, A.A., Viswanadhan, N.A., Thomas, L.B., Guzman, R.D., Deland, L.A., Mastorides, S.M.: Using artificial intelligence for covid-19 chest x-ray diagnosis. Fed. Pract. **37**(9), 398 (2020)
38. Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., Summers, R.M.: ChestX-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE (2017). https://doi.org/10.1109/cvpr.2017.369
39. Pneumonia detection challenge database. RSNA: Radiological Society of North America (2018). https://www.kaggle.com/c/rsnapneumonia-detection-challenge/. Accessed 10 April 2021
40. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z.: Rethinking the inception architecture for computer vision. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE (2016). https://doi.org/10.1109/cvpr.2016.308
41. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE (2016). https://doi.org/10.1109/cvpr.2016.90
42. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization (2014). arXiv preprint arXiv:1412.6980
43. Marcel, S., Rodriguez, Y.: Torchvision the machine-vision package of torch. In: Proceedings of the international conference on Multimedia—MM '10. ACM Press (2010). https://doi.org/10.1145/1873951.1874254
44. Chowdhury, M.E.H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M.A., Mahbub, Z.B., Islam, K.R., Khan, M.S., Iqbal, A., Emadi, N.A., Reaz, M.B.I., Islam, M.T.: Can AI help in screening viral and COVID-19 pneumonia? IEEE Access **8**, 132665–132676 (2020). https://doi.org/10.1109/access.2020.3010287

45. Kermany, D.S., Goldbaum, M., Cai, W., Valentim, C.C., Liang, H., Baxter, S.L., McKeown, A., Yang, G., Wu, X., Yan, F., Dong, J., Prasadha, M.K., Pei, J., Ting, M.Y., Zhu, J., Li, C., Hewett, S., Dong, J., Ziyar, I., Shi, A., Zhang, R., Zheng, L., Hou, R., Shi, W., Fu, X., Duan, Y., Huu, V.A., Wen, C., Zhang, E.D., Zhang, C.L., Li, O., Wang, X., Singer, M.A., Sun, X., Xu, J., Tafreshi, A., Lewis, M. A., Xia, H., Zhang, K.: Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell **172**(5), 1122–1131.e9 (2018). https://doi.org/10.1016/j.cell.2018.02.010
46. Nguyen, H.Q., Lam, K., Le, L.T., Pham, H.H., Tran, D.Q., Nguyen, D.B., Le, D.D., Pham, C.M., Tong, H.T., Dinh, D.H., et al.: Vindr-cxr: An open dataset of chest x-rays with radiologist's annotations (2020). arXiv preprint arXiv:2012.15029. https://www.kaggle.com/c/vinbigdata-chest-xray-abnormalities-detection/. Accessed 20 March 2021
47. Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., Pedreschi, D.: A survey of methods for explaining black box models. ACM Comput. Surv. **51**(5), 1–42 (2019). https://doi.org/10.1145/3236009
48. Gilpin, L.H., Bau, D., Yuan, B.Z., Bajwa, A., Specter, M., Kagal, L.: Explaining explanations: An overview of interpretability of machine learning. In: 2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA). IEEE (2018). https://doi.org/10.1109/dsaa.2018.00018
49. Selvaraju, R.R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., Batra, D.: Grad-CAM: visual explanations from deep networks via gradient-based localization. In: 2017 IEEE International Conference on Computer Vision (ICCV). IEEE (2017). https://doi.org/10.1109/iccv.2017.74
50. Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., Bai, J., Lu, Y., Fang, Z., Song, Q., Cao, K., Liu, D., Wang, G., Xu, Q., Fang, X., Zhang, S., Xia, J., Xia, J.: Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy. Radiology **296**(2), E65–E71 (2020). https://doi.org/10.1148/radiol.2020200905
51. Gunraj, H., Sabri, A., Koff, D., Wong, A.: Covid-net ct-2: Enhanced deep neural networks for detection of covid-19 from chest ct images through bigger, more diverse learning. arXiv preprint arXiv:2101.07433 (2021)
52. Modegh, R.G., Hamidi, M., Masoudian, S., Mohseni, A., Lotfalinezhad, H., Kazemi, M.A., Moradi, B., Ghafoori, M., Motamedi, O., Pournik, O., et al.: Accurate and rapid diagnosis of covid-19 pneumonia with batch effect removal of chest ct-scans and interpretable artificial intelligence (2020). arXiv preprint arXiv:2011.11736
53. Harmon, S.A., Sanford, T.H., Xu, S., Turkbey, E.B., Roth, H., Xu, Z., Yang, D., Myronenko, A., Anderson, V., Amalou, A., Blain, M., Kassin, M., Long, D., Varble, N., Walker, S.M., Bagci, U., Ierardi, A.M., Stellato, E., Plensich, G.G., Franceschelli, G., Girlando, C., Irmici, G., Labella, D., Hammoud, D., Malayeri, A., Jones, E., Summers, R.M., Choyke, P.L., Xu, D., Flores, M., Tamura, K., Obinata, H., Mori, H., Patella, F., Cariati, M., Carrafiello, G., An, P., Wood, B.J., Turkbey, B.: Artificial intelligence for the detection of COVID-19 pneumonia on chest CT using multinational datasets. Nat. Commun. **11**(1) (2020). https://doi.org/10.1038/s41467-020-17971-2
54. Wang, X., Deng, X., Fu, Q., Zhou, Q., Feng, J., Ma, H., Liu, W., Zheng, C.: A weakly-supervised framework for COVID-19 classification and lesion localization from chest CT. IEEE Trans. Med. Imaging **39**(8), 2615–2625 (2020). https://doi.org/10.1109/tmi.2020.2995965
55. Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., Yu, L., Ni, Q., Chen, Y., Su, J., Lang, G., Li, Y., Zhao, H., Liu. J., Xu, K., Ruan, L., Sheng, J., Qiu, Y., Wu, W., Liang, T., Li, L.: A deep learning system to screen novel coronavirus disease 2019 pneumonia. Engineering **6**(10), 1122–1129 (2020). https://doi.org/10.1016/j.eng.2020.04.010
56. X. Li, Y. Zhou, P. Du, G. Lang, M. Xu, and W. Wu, "A deep learning system that generates quantitative CT reports for diagnosing pulmonary tuberculosis," *Applied Intelligence*, vol. 51, no. 6, pp. 4082–4093, 2021. [Online]. Available: https://doi.org/10.1007/s10489-020-02051-1
57. Gunraj, H., Wang, L., Wong, A.: COVIDNet-CT: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest CT images. Frontiers in Medicine **7** (2020). https://doi.org/10.3389/fmed.2020.608525

58. Arik, S.O., Li, C.-L., Yoon, J., Sinha, R., Epshteyn, A., Le, L.T., Menon, V., Singh, S., Zhang, L., Yoder, N., et al.: Interpretable sequence learning for covid-19 forecasting (2020). arXiv preprint arXiv:2008.00646
59. Snider, B., Phillips, P., MacLean, A., McBean, E., Gadsden, S.A., Yawney, J.: Artificial intelligence to predict the risk of mortality from covid-19: Insights from a Canadian application (2020). https://doi.org/10.1101/2020.09.29.20201632
60. Hwang, W., Lei, W., Katritsis, N.M., MacMahon, M., Chapman, K., Han, N.: Current and prospective computational approaches and challenges for developing COVID-19 vaccines. Adv. Drug Deliv. Rev. **172**, 249–274 (2021). https://doi.org/10.1016/j.addr.2021.02.004
61. Wang, C.J., Ng, C.Y., Brook, R.H., Response to COVID-19 in Taiwan. JAMA **323**(14) 1341 (2020). https://doi.org/10.1001/jama.2020.3151
62. Wang, W., Wang, Y., Zhang, X., Li, Y., Jia, X., Dang, S.: WeChat, a Chinese social media, may early detect the SARS-CoV-2 outbreak in 2019 (2020). https://doi.org/10.1101/2020.02.24.20026682
63. Ciaffi, J., Meliconi, R., Landini, M.P., Ursini, F.: Google trends and COVID-19 in Italy: could we brace for impact? Intern. Emerg. Med. **15**(8), 1555–1559 (2020). https://doi.org/10.1007/s11739-020-02371-7
64. Beyan, C., Bustreo, M., Shahid, M., Bailo, G.L., Carissimi, N., Bue, A.D.: Analysis of face-touching behavior in large scale social interaction dataset. In: Proceedings of the 2020 International Conference on Multimodal Interaction. ACM (2020). https://doi.org/10.1145/3382507.3418876
65. Raamkumar, A.S., Tan, S.G., Wee, H.L.: Use of health belief model-based deep learning classifiers for COVID-19 social media content to examine public perceptions of physical distancing: model development and case study. JMIR Public Health Surveill. **6**(3), e20493 (2020). https://doi.org/10.2196/20493
66. Jelodar, H., Wang, Y., Orji, R., Huang, S.: Deep sentiment classification and topic discovery on novel coronavirus or covid-19 online discussions: Nlp using lstm recurrent neural network approach. IEEE J. Biomed. Health Inform. **24**(10), 2733–2742 (2020)
67. Bhattacharya, S., Maddikunta, P.K.R., Pham, Q.-V., Gadekallu, T.R., S.R.K.S., Chowdhary, C.L., Alazab. M., Piran, M.J.: Deep learning and medical image processing for coronavirus (COVID-19) pandemic: a survey. Sustain. Cities Soc. **65**, 102589 (2021). https://doi.org/10.1016/j.scs.2020.102589
68. Raman, R., Achuthan, K., Vinuesa, R., Nedungadi, P.: COVIDTAS COVID-19 tracing app scale—an evaluation framework. Sustainability **13**(5), 2912 (2021). https://doi.org/10.3390/su13052912
69. Vinuesa, R., Theodorou, A., Battaglini, M., Dignum, V.: A socio-technical framework for digital contact tracing. Results Eng. **8**, 100163 (2020). https://doi.org/10.1016/j.rineng.2020.100163
70. Ates, H.C., Yetisen, A.K., Güder, F., Dincer, C.: Wearable devices for the detection of COVID-19. Nat. Electron. **4**(1), 13–14 (2021). https://doi.org/10.1038/s41928-020-00533-1
71. Best, J.: Wearable technology: covid-19 and the rise of remote clinical monitoring. BMJ, p. n413 (2021). https://doi.org/10.1136/bmj.n413
72. Un, K.-C., Wong, C.-K., Lau, Y.-M., Lee, J.C.-Y., Tam, F.C.-C., Lai, W.-H., Lau, Y.-M., Chen, H., Wibowo, S., Zhang, X., Yan, M., Wu, E., Chan, S.-C., Lee, S.-M., Chow, A., Tong, R.C.-F., Majmudar, M.D., Rajput, K.S., Hung, I.F.-N., Siu, C.-W.: Observational study on wearable biosensors and machine learning-based remote monitoring of COVID-19 patients. Scientific Reports **11**(1) (2021). https://doi.org/10.1038/s41598-021-82771-7
73. Jeong, H., Rogers, J.A., Xu, S.: Continuous on-body sensing for the COVID-19 pandemic: gaps and opportunities. Sci. Adv. **6**(36), eabd4794 (2020). https://doi.org/10.1126/sciadv.abd4794
74. Hu, Y., Jacob, J., Parker, G.J., Hawkes, D.J., Hurst, J.R., Stoyanov, D.: The challenges of deploying artificial intelligence models in a rapidly evolving pandemic. Nat. Mach. Intell. **2**(6), 298–300 (2020)

COVID-19 Features Detection Using Machine Learning Models and Classifiers

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Abstract Different machine learning techniques and approaches were implemented to detect the features of COVID-19, from chest X-Ray and CT medical images, as well as to identify them from other similar human-being lungs infection diseases. In this work, Logistic Regression, Neural Networks, Random Forests, Decision Trees, kNN, and CN2 Rule Induction are the machine learning models and classifiers that were utilized to perform such detection and identification. The entire process according to the importance of good parameters selection, and such performance was presented and emphasized at different phases of models analysis and visualization. In our presented method, the achieved classification accuracies were up to 95.5%. Our work was implemented using Orange software, as a visual-based tool, and dedicated for physicians with no experience in machine learning algorithms and programming languages.

Keywords Coronavirus · COVID-19 · Features detection · Features extraction · Machine learning classifiers

1 Introduction

The Coronavirus disease pandemic, a.k.a. *COVID-19* by WHO (World Health Organization) [1], is world widely spread affecting many people in different countries. Since this virus does not have a well-known information as well as not match any similar symptoms that occur by other well-documented and knowledge-based viruses, medical concerns and emergency orders were firmly raised in many regions, e.g. schools and businesses closures as well as stay-home orders, to protect lives

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and eliminate the disease outbreak excessively as well. For that, hourly data collections regarding infected areas, communities, and people are continuously gathered, accumulated, and compiled to form visual representations of COVID-19 morbidness cases and their spreading in different zones.

From the scientific and engineering point of view, the machine learning algorithms and models can play a role in classifying and identifying the COVID-19 cases from other similar human-being lungs infection diseases, such as Bacterial Pneumonia, Viral Pneumonia, Pneumocystis, Streptococcus, and SARS, using chest X-Ray and CT (Computerized Tomography) medical images. Some researchers were able to have fairly classified results from such diagnostic images using different models of ImageNet deep learning classifiers [2, 3], as described in [4–6]. Alimadadi et al. stated how governments, research institutes, and technological companies issued an urgent call-to-action for AI (Artificial Intelligence) researchers to develop data mining techniques and build open-source real-time analytical datasets to fight the COVID-19 pandemic and stop its spreading. Such that, the collection of large real-time diagnostic datasets of COVID-19 cases can give a better understanding of the COVID-19 patterns and spreading, as well as improve the speed and accuracy of the medical analyses when such diagnostic datasets are integrated with machine learning algorithms [7]. Pinter et al. mentioned that due to the lack of necessarily diagnostically datasets collection, the epidemiological models were in challenge in the matter of higher accuracy delivery for a long-term prediction. They implemented the ANFIS (Adaptive Neural-Fuzzy Inference System) and MLP-ICA (Multi-Layer Perceptron-Imperialist Competitive Algorithm) as a hybrid machine learning algorithms approach to predict the time-series of the infected individuals and their mortality rates, using MATLAB's ANFIS toolbox. Moreover, their work can be considered as an initial benchmarking tool for future research regarding the potential of machine learning algorithms in COVID-19 pandemic prediction [8]. In the paper of Elaziz et al., a new machine learning method was presented to classify the COVID-19 and non-COVID-19 cases using chest X-ray images. The features extracted from such images using the method of FrMEMs (Fractional Multichannel Exponent Moments) within a parallel workstation to accelerate the overall computational process. Their work was evaluated using two COVID-19 chest X-ray datasets that achieved accuracy rates of 96.09% and 98.09% for the first and second datasets, respectively [9]. Sujath et al. presented a model to predict the spread of COVID-19 in India, this approach was implemented using different machine learning models, such as Linear Regression, MLP, and Vector Autoregression using the COVID-19 Kaggle repository datasets for the epidemiological COVID-19 cases in India, only. Their work showed that the CI (Confidence Interval), a way of quantifying the uncertainty of estimated results, was 95% for the completely implemented machine learning models [10]. Ardabili et al. presented a comparative analysis of different machine learning models, such as MLP and ANFIS, and soft computing models, such as GA (Genetic Algorithm), PSO (Particle Swarm Optimization), and GWO (Grey Wolf Optimizer), to predict the COVID-19 outbreak and spreading. They demonstrated that the machine learning algorithms were effective tools and have more promising results than the soft computing models in the COVID-19 pandemic prediction [11]. Brinati et al. described the amplification of

COVID-19 viral RNA using the rRT–PCR (real-time Reverse Transcription–Polymerase Chain Reaction) is the current gold standard test for COVID-19 infections confirmation. However, due to the rRT-PCR weaknesses, such as false-negative rates of 15–20%, and a potential shortage of reagents, therefore faster, less expensive, and more accessible testing methods, as alternative solutions, should be developed. Two machine learning models were implemented to classify patients as either positive or negative to the COVID-19 infection using the hematochemical values from the routine blood exams. In such two models, the accuracy ranges 82–86% and the sensitivity ranges 92–95% with respect to the gold standard test. Moreover, a Decision Tree model was implemented as straightforward simple decision assistance for the COVID-19 suspected cases [12]. Cheng et al. indicated that approximately 20–30% of COVID-19 infected cases need hospitalization, while 5–12% of them may require critical care in the ICU (Intensive Care Unit). In their work, they developed a machine learning algorithm, as a risk prioritization tool, using Random Forest model to predict the ICU requirements within the 24-h. Time-series information, laboratory data, vital signs, nursing valuations, and ECG (Electrocardiograms) signals were used as input datasets for this model. These datasets were randomly split into 70% of the training dataset and 30% of the test dataset. Then, this model was trained using the tenfold CV (Cross-Validation) technique. The model's performance and prediction was evaluated on the test dataset, as the following: sensitivity of 72.8% (95% CI: 63.2–81.1%), specificity of 76.3% (95% CI: 74.7–77.9%), accuracy of 76.2% (95% CI: 74.6–77.7%), and Area under ROC of 79.9% (95% CI: 75.2–84.6%). Thus, this machine learning tool could improve the planning and the management of hospital resources in more effective ways regarding the COVID-19 patients' hospitalization [13]. In the study of Rustam et al., different supervised machine learning models were implemented to forecast the number of patients infected by COVID-19. Four standard models, such as Linear Regression, Exponential Smoothing, LASSO (Least Absolute Shrinkage and Selection Operator), and SVM (Support Vector Machine), were developed to forecast the upcoming patients and results. The number of newly infected patients, the number of recovered patients in the next 10 days, and the number of deaths were the three prediction categories for each model. The Exponential Smoothing model had better forecasting results than the other models, followed by the Linear Regression model, and then the LASSO model performed well in forecasting the newly infected cases, recovery rate, and death rate. While the SVM model performed poorly in the three prediction categories. The three models were performed on the Johns Hopkins University's COVID-19 repository datasets [14].

2 Materials and Methods

A large set of diagnostic medical images of human-being lungs diseases, i.e. *datasets*, has to be publicly provided to the scientific communities, to achieve the valuable comparable results of identification and classification of COVID-19 cases. For this reason, many medical datasets [15, 16] have been already published to stop the

COVID-19 outbreak using vast sets of technologies and applied approaches, e.g. machine learning algorithms. The aim of our work is to identify the best classifiers, within the best CA (Classification Accuracy) scores, that classify the COVID-19 infected cases from other human-being lungs infected cases. As well as to provide a convenient visual-based classification tool to physicians, without their need to understand the deep knowledge of machine learning algorithms, the programming languages, such as Python, the computational libraries, such as NumPy, Pandas, and scikit-learn, and the abstraction platforms, such as PyTorch and TensorFlow. Our work was fully designed, built, and implemented using the open-source machine learning and data visualization tool *Orange*, from the University of Ljubljana [17].

Orange provides data analysis, data visualization, statistical distributions, and vast sets of plotting tools, as well as its GUI (Graphical User Interface) allows the physicians to focus on data analysis and manipulating, instead of coding, to accelerate the diagnostically identification and classification workflows with ease. Our presented work with Orange was performed using the datasets that were provided by the Kaggle repository [15], and the workflow was categorized into four proposed phases: (1) Datasets Preparation Phase, (2) Training Dataset Operations Phase, (3) Test Dataset Operations Phase, and (4) Prediction and Performance Phase. Furthermore, seven machine learning algorithms were utilized, in this work, to have sufficient comparable decisions regarding the best-chosen model for the best classification accuracy to identify and classify the COVID-19 cases. These models are:

- *Distances* that computes the distances between the rows and columns in the datasets, i.e. the cases [18, 19],
- *Logistic Regression* that classifies the cases using the non-linear Sigmoid function (σ) [19, 20],
- *CN2 Rule Induction* that uses efficient induction of simple and comprehensive rules in the form of (IF *condition* THEN *predict case*) to predict the cases [21, 22],
- *Tree* that splits the cases into nodes and leaves by labeling purity and forward pruning [23, 24],
- *Random Forest* that classifies the cases using an ensemble of decision trees [25, 26],
- *kNN* (k-Nearest Neighbors) that searches for the k closest cases based on their features and their averages as classification factors [27, 28], and
- *Neural Network* that classifies the cases within the MLP model using the backpropagation method [29].

Note that all the aforementioned algorithms are supervised classifiers, except the *Distances*, which is an unsupervised classifier.

Note that some of Orange's toolboxes have been renamed in purpose to match their underlying phases as well as their designated operations, for ease of follow and understanding.

2.1 Datasets Preparation Phase

The datasets were gathered from the chest X-Ray (of PA “Posteroanterior”, AP “Anteroposterior”, APS “AP Supine”, and L “Lateral” captures [30]) and CT (of Axial and Coronal scans [31]) medical images of COVID-19, SARS, Pneumocystis, and Streptococcus infection cases. Since the number of these gathered images is relatively small, the data augmentation technique is performed in this phase. The data augmentation was achieved by enlarging the size of each medical image, i.e. *sample*, in the datasets by increasing their (1) *brightness* by the factor of 16 and (2) *contrast* by the factor of 32, to have a sufficient number of samples. A sufficient number of samples yields a good identification and better classification accuracy judgment, as well as fulfills Hoeffding’s Inequality generalization bound [32]. For instance, to demonstrate Hoeffding’s Inequality, for any randomly selected size of N COVID-19 and non-COVID-19 samples, the generalization bound for the probability ($P[\cdot]$) of such an event for any tolerance ($\epsilon > 0$) is as stated in Eq. (1):

$$P[|v - \mu| > \epsilon] \leq 2e^{-2\epsilon^2 N} \tag{1}$$

where, μ is the probability of the COVID-19 samples in a bin consisting of COVID-19 and non-COVID-19 samples, while v is the fraction of the selected COVID-19 samples among the non-COVID-19 samples. Note that Hoeffding’s Inequality formula mostly affects by how large N and the chosen ϵ are.

The ACDSee® photo editing software was used to implement such data augmentation [33]. Note that other data augmentation methods, such as shape sheering, angles rotation, and flipping/mirroring, were not used in this phase, due to the fact that physicians usually check such diagnostic images in the normal straightway position, as portraits. For fast data processing, the samples were scaled uniformly to the dimensions of 128 × 128 pixels, and the resultant statistics of these samples are summarized in Table 1.

Figure 1 demonstrates the preparation phase of these datasets that consists of the following Orange toolboxes: (1) *Import Images* that loads the datasets locally, i.e. from the computer, (2) *Image Viewer* that visually checks the loaded datasets, (3) *Adding Labels* that generates the cases for each sample. Since these datasets are non-labeled and most of the classifiers are supervised, then a column of labels, i.e. *classes*, was generated regarding the samples’ filenames. Note that, each filename

Table 1 Infected samples statistics

Infection case	Number of samples
COVID-19	169
SARS	33
Pneumocystis	45
Streptococcus	51
Total =	298

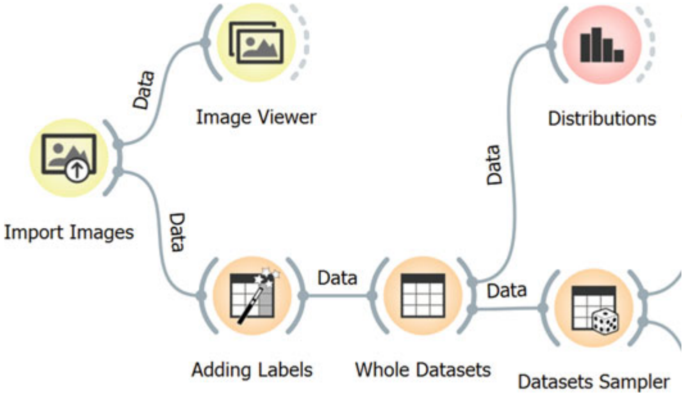


Fig. 1 Datasets preparation phase using orange toolboxes

corresponds to an infected case name, for instance the filename of the "COVID-19-APSupine-Xray-1.jpeg" sample generates the "COVID-19" case as a label. (4) *Whole Datasets* that lists the whole labeled datasets, (5) *Distributions* that statistically displays the labeled datasets, and (6) *Datasets Sampler* that samples the whole labeled datasets into 70% of training dataset and 30% of test dataset, i.e. 209 training samples and 89 test samples.

For more illustration, Fig. 2 illustrates the *Image Viewer* and *Adding Labels* toolboxes of Orange.

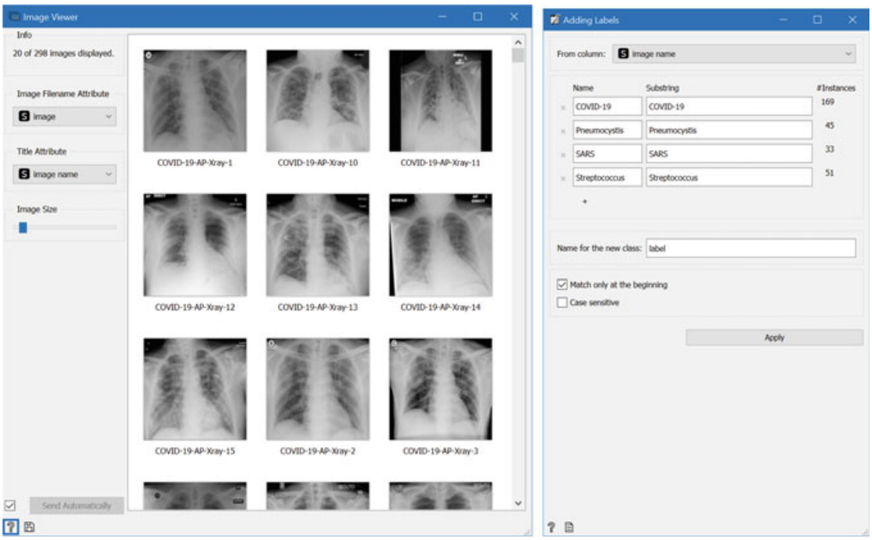
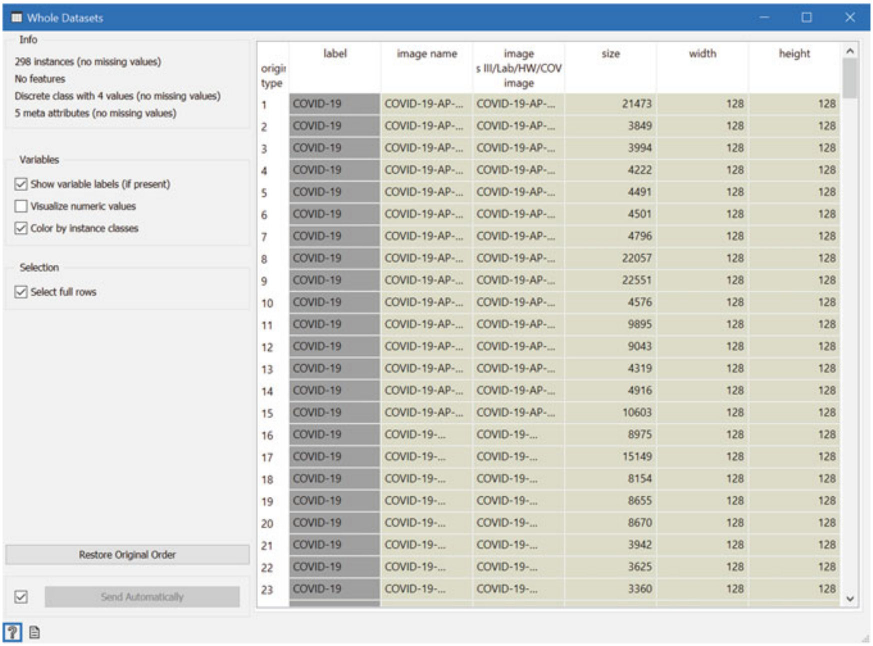


Fig. 2 Orange image viewer (left) and adding labels (right) toolboxes



origi type	label	image name	image s III/Lab/HW/COV image	size	width	height
1	COVID-19	COVID-19-AP-...	COVID-19-AP-...	21473	128	128
2	COVID-19	COVID-19-AP-...	COVID-19-AP-...	3849	128	128
3	COVID-19	COVID-19-AP-...	COVID-19-AP-...	3994	128	128
4	COVID-19	COVID-19-AP-...	COVID-19-AP-...	4222	128	128
5	COVID-19	COVID-19-AP-...	COVID-19-AP-...	4491	128	128
6	COVID-19	COVID-19-AP-...	COVID-19-AP-...	4501	128	128
7	COVID-19	COVID-19-AP-...	COVID-19-AP-...	4796	128	128
8	COVID-19	COVID-19-AP-...	COVID-19-AP-...	22057	128	128
9	COVID-19	COVID-19-AP-...	COVID-19-AP-...	22551	128	128
10	COVID-19	COVID-19-AP-...	COVID-19-AP-...	4576	128	128
11	COVID-19	COVID-19-AP-...	COVID-19-AP-...	9895	128	128
12	COVID-19	COVID-19-AP-...	COVID-19-AP-...	9043	128	128
13	COVID-19	COVID-19-AP-...	COVID-19-AP-...	4319	128	128
14	COVID-19	COVID-19-AP-...	COVID-19-AP-...	4916	128	128
15	COVID-19	COVID-19-AP-...	COVID-19-AP-...	10603	128	128
16	COVID-19	COVID-19-...	COVID-19-...	8975	128	128
17	COVID-19	COVID-19-...	COVID-19-...	15149	128	128
18	COVID-19	COVID-19-...	COVID-19-...	8154	128	128
19	COVID-19	COVID-19-...	COVID-19-...	8655	128	128
20	COVID-19	COVID-19-...	COVID-19-...	8670	128	128
21	COVID-19	COVID-19-...	COVID-19-...	3942	128	128
22	COVID-19	COVID-19-...	COVID-19-...	3625	128	128
23	COVID-19	COVID-19-...	COVID-19-...	3360	128	128

Fig. 3 Orange whole datasets toolbox

Note that four labels were generated using *Adding Labels* toolbox with labels as *COVID-19*, *Pneumocystis*, *SARS*, and *Streptococcus*. Figure 3 shows the *Whole Datasets* toolbox of Orange

Finally, Fig. 4 demonstrates the *Distributions* and *Datasets Sampler* toolboxes of Orange.

2.2 *Training Dataset Phase*

After the 209 samples, i.e. the training dataset, were received from the *Datasets Sampler* toolbox from the Datasets Preparation Phase, they can be buffered and visually checked along with their generated labels using the *Training Dataset* toolbox. Since these training samples contain no useful classifiable information, the *Inception v3 Model (Training)* toolbox is in need to represent this training dataset into its vectorized equivalent representations, a.k.a. *features*. This toolbox generates 2048 numerical features for each sample that makes the next classification processes more meaningful, and such features can be viewed using the *Training Dataset Features* toolbox of Orange. Note that the *Inception v3 Model (Training)* toolbox is based on Google's Inception v3 CNN (Convolutional Neural Network) architecture [34] that is trained on ImageNet.

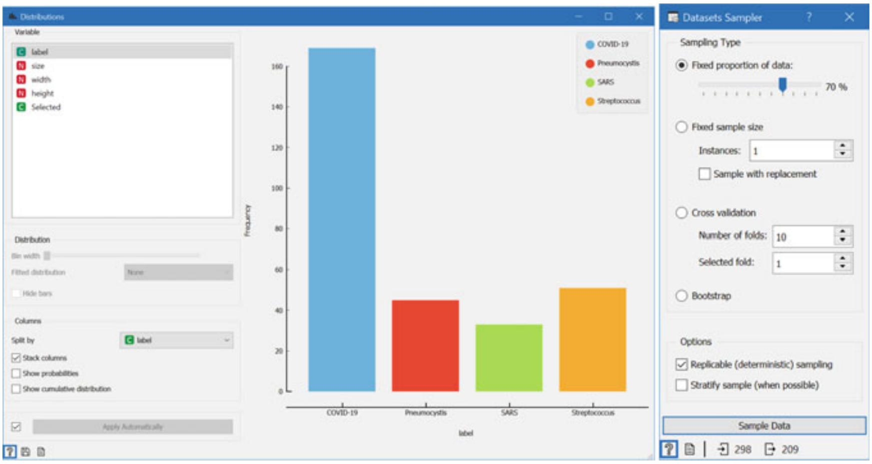


Fig. 4 Orange distributions (left) and datasets sampler (right) toolboxes, the sampling percentage can be changed based on the model design and technical requirements

Then, these features along with their labels from the *Inception v3 Model (Training)* toolbox were fed to various machine learning classifiers for further identification and classification of training dataset based on their features (and labels, if they were supervised classifiers), as shown in Fig. 5. Note that, the calculated distances in the *Distances* classifier were visualized using the *Hierarchical Clustering* toolbox along with the *Hierarchical Clustering Viewer* toolbox, the generated rules in the *CN2 Rule Induction* classifier were viewed through the *CN2 Rule Viewer* toolbox, the generated tree with nodes and leaves in the *Tree* classifier were visualized using the *Tree Viewer* toolbox.

2.3 Test Dataset Phase

After the 89 samples, i.e. the test dataset, were received from the *Datasets Sampler* toolbox from the Datasets Preparation Phase, they can be buffered and visually checked along with their labels using the *Test Dataset* toolbox, as shown in Fig. 6. Since these test samples contain no useful classifiable information, the *Inception v3 Model (Test)* toolbox was applied here, and their features can be viewed within the *Test Dataset Features* toolbox.

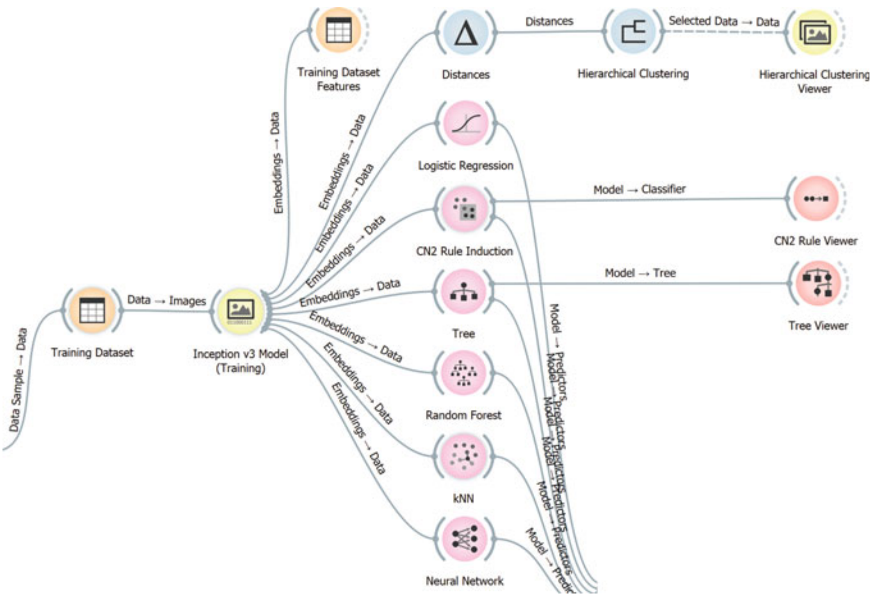


Fig. 5 Training Dataset Operations Phase using Orange toolboxes, (left) the training dataset was fed from the first phase then propagated to the Inception v3 Model for features generating, (middle) predictions were calculated from the machine learning classifiers then forwarded to the fourth phase for classification accuracies, (right) and the distances, rules, and trees can be viewed through the viewers

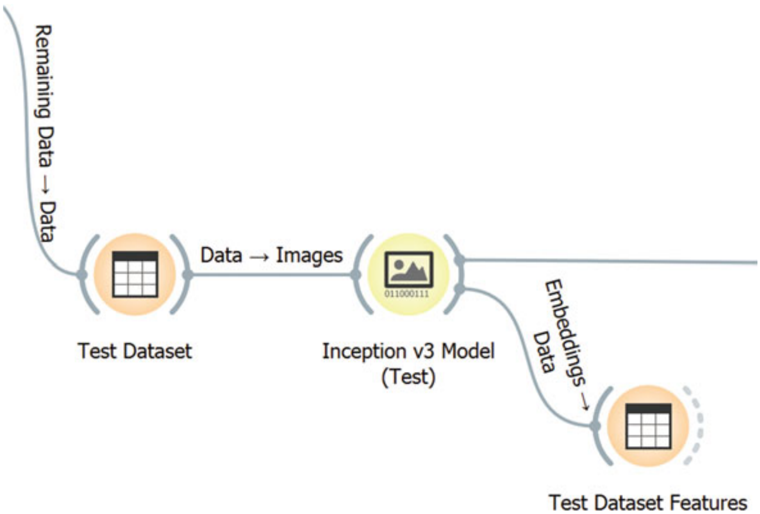


Fig. 6 Test Dataset Operations Phase using Orange toolboxes, (left) the test dataset was fed from the first phase, (middle) then propagated to the Inception v3 Model for features generating that fed to the fourth phase for performance measurement, (right) and these features can be visually viewed using test Dataset Features toolbox

2.4 Prediction and Performance Phase

The received signals from the Training Dataset Phase, i.e. the predictions from the machine learning classifiers, as well as from the Test Dataset Phase, i.e. the features from the *Inception v3 Model (Test)* toolbox were fed to the *Predictions* toolbox, to measure the performance and score the classification accuracies regarding the best-chosen classifier for COVID-19 cases. The following Orange toolboxes were implemented to compute such measurement and scoring, as illustrated in Fig. 7:

- *Confusion Matrix*: Shows the numbers of matched and unmatched samples from the test dataset under the predicted and the actual cases that were judged by the *Predictions* toolbox [35].
- *Sieve Diagram*: Visualizes the frequencies of cases based on a pair of classifiers [36].
- *Linear Projection*: Plots the linear separation of cases concerning their classifiers [37].

3 Methodology

In our presented work, an appropriate visual-based classification tool is provided that targets the medical domain, especially for the physicians with less experience in the machine learning philosophy and limited programming skills. Different distances, rules, trees, tables, and plots were obtained from the proposed seven machine learning classifiers based on their different selection of parameters. For that, the following

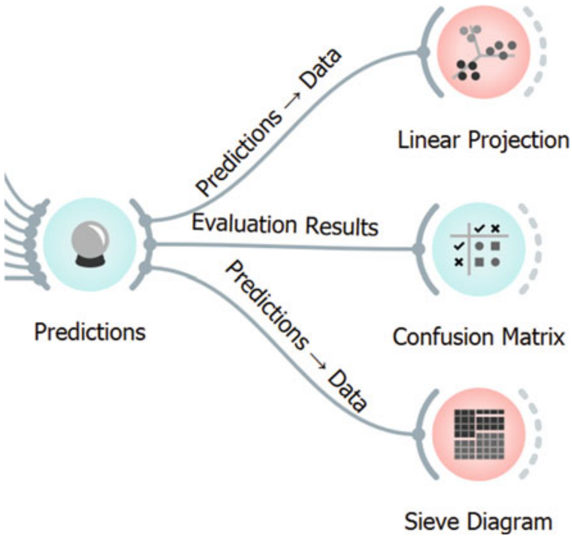


Fig. 7 Prediction and Performance Phase using Orange toolboxes, (left) the signals were received from the second and third phases, (right) and then the performance measurement and classification accuracies scoring were achieved through these three toolboxes

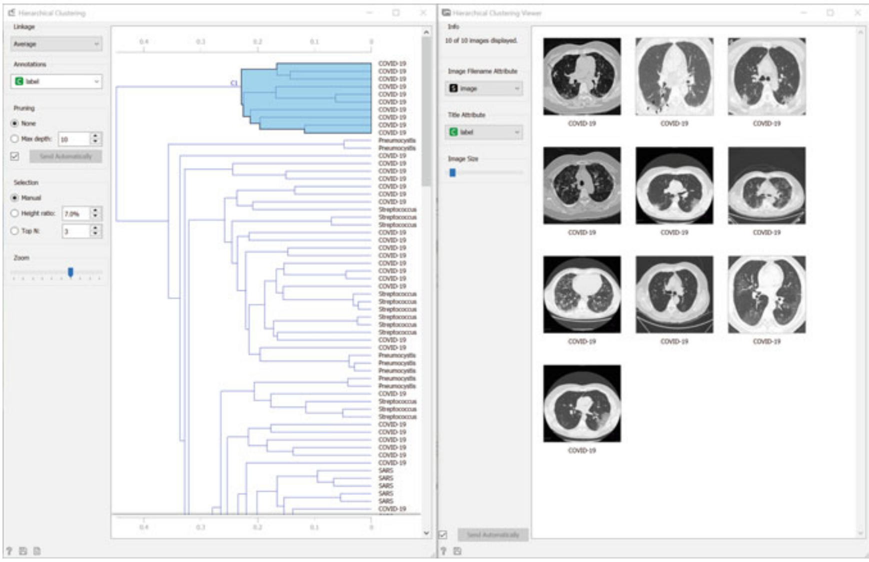


Fig. 8 Distances and hierarchical clustering results of COVID-19 axial CT scans of 100% accuracy

configurable parameters for each machine learning classifier were chosen and tuned to have the best human-classifiable results regarding COVID-19 infection cases among other similar human-being lungs infection cases. Note that some parameters have an insignificant effect or no effect at all on the classification results for some classifiers.

3.1 Parameters of Distances Classifier

The *Distances* toolbox, along with the *Hierarchical Clustering* and *Hierarchical Clustering Viewer* toolboxes, performs a good classification on the training dataset with a small number of errors in clustering the cases, as demonstrated in Figs. 8, 9, and 10. Few cases in the clustering process have mismatched results, and the explanations of these outcomes were left to the epidemiology specialists due to their deep knowledge in this field. Our work provides an adequate and easy-to-use tool for them. Note that the *Distance Metric* parameter is better to be set as *Cosine* when dealing with images, in general.

3.2 Parameters of CN2 Rule Induction Classifier

The *CN2 Rule Induction* toolbox produces different rules, in the format of (IF *condition* THEN *predict case*), and classification accuracies based on its *Evaluation measure* parameter. Such that, when this parameter was set to *Entropy* [38] its

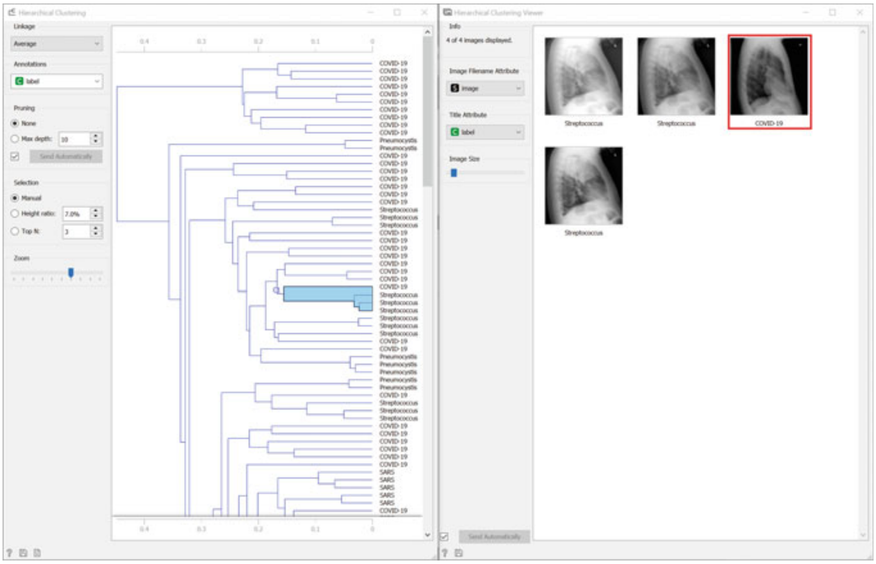


Fig. 9 Distances and hierarchical clustering results of streptococcus L X-Ray images with one mismatched case

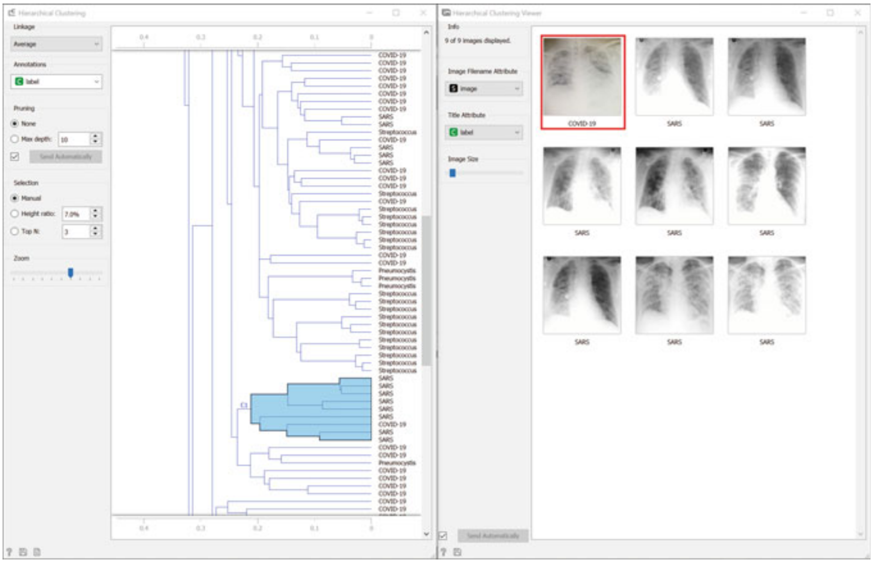


Fig. 10 Distances and hierarchical clustering results of SARS PA X-Ray images with one mismatched case

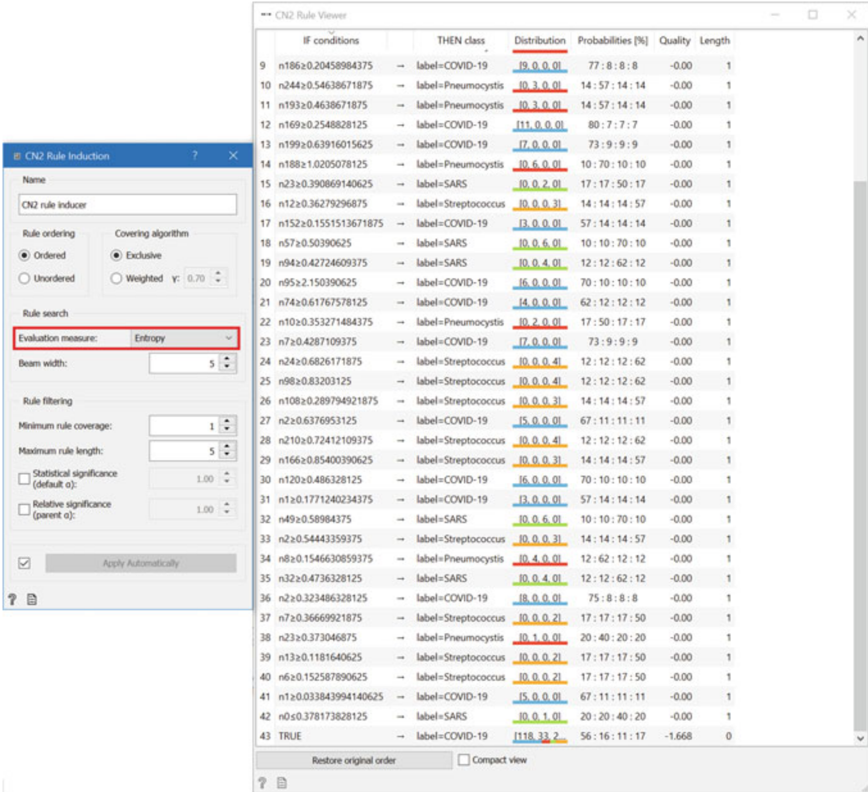


Fig. 11 CN2 Rule Induction and Evaluation measure parameter as Entropy, lower classification accuracy and higher induced difficult-to-read rules

classification accuracy was 53.9% and the generated number of rules was 43, as shown in Fig. 11. However, when this parameter was set to *Laplace accuracy* [38], its classification accuracy changed to 64% and the generated number of rules to 19, as shown in Fig. 12. Therefore, the *Laplace accuracy* parameter produces more classification accuracy results with fewer easy-to-read induced classifiable rules. Note that, the colored bars in the *Distribution* column represent the infection case: Blue for COVID-19, Green for SARS, Orange for Streptococcus, and Red for Pneumocystis.

3.3 Parameters of Random Forest Classifier

The parameter *Number of trees* does not influence at all on the *Random Forest* toolbox CA performance and its results. Such that, when this parameter was set to 10, its CA is 70.8%. While, when this parameter was set to 20, its CA still be at 70.8%.

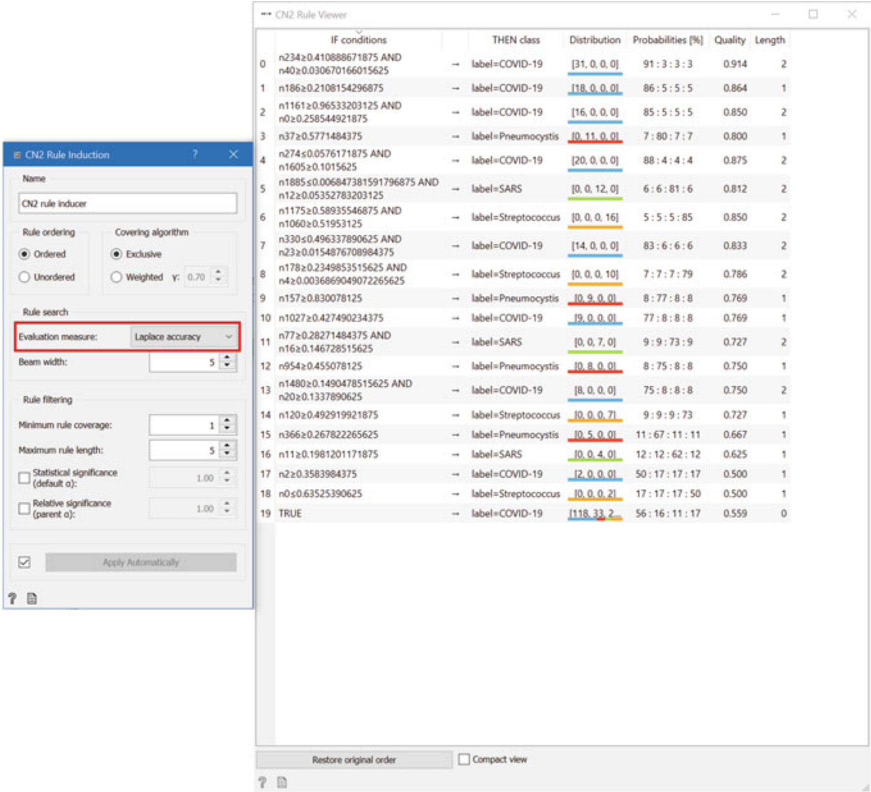


Fig. 12 CN2 Rule Induction and Evaluation measure parameter as Laplace accuracy, higher classification accuracy and a few induced easy-to-read rules

3.4 *Parameters of Tree Classifier*

The *Min. number of instances in leaves* parameter has no huge influence on the *Tree* toolbox's CA performance and its results. Such that, when this parameter was set to 2, its CA is 58.4% with a tree generating of 35 nodes and 18 leaves. While, when this parameter set to 3, its CA changed to 59.6% with the same tree of 35 nodes and 18 leaves, as illustrated in Fig. 13.

The interpretability rules that generate the unbalanced binary tree, as shown in Fig. 13, will be as follows:

- The parent node, *root*, generates the left-side child, *node*, when ($n21 \leq 0.283447$).
- The root generates the right-side node when ($n21 > 0.283447$).
- The left-side and right-side nodes then generate their children in the same fashion, and so on …

According to these interpretability rules, the percentile of cases was calculated based on the *nXXXX*. Note that the *n21*, for instance, is one of the 2048 features

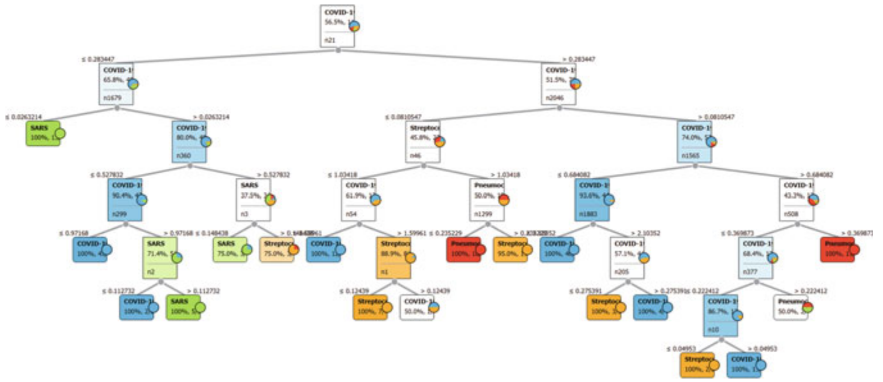


Fig. 13 Orange Tree viewer toolbox of 35 nodes and 18 leaves tree at either 2 or 3 of the Min. number of instances in leaves parameter selection

Table 2 CA based on Number of neighbors and Weight parameters

Number of neighbors	Weights	
	Uniform	Distance
5	68.5%	75.3%
10	61.8%	75.3%

that were obtained previously from the *Inception v3 Model (Training)* toolbox on the training dataset.

3.5 Parameters of kNN Classifier

The *kNN* toolbox produces different CA based on *Number of neighbors* and *Weight* parameters. Table 2 presents the generated CA based on these two parameters. Note that, there were insignificant changes in its CA for the 5 or 10 selection of the *Number of neighbors* parameter as well as for the *Uniform* or *Distance* selection of the *Weight* parameter.

3.6 Parameters of Logistic Regression Classifier

The *Logistic Regression* toolbox generates different CA depending on the *Regularization type* parameter. Therefore, when this parameter was set to *Ridge (L2)* [39], then its CA was 95.5%. While, when this parameter was set to *Lasso (L1)* [40] then its CA changed be 84.3%. Since the *Lasso (L1)* parameter shrinks the extreme values of each sample towards its central values, then this could cause the loss of important information during the classification process than the *Ridge (L2)* parameter. Note that the *Strength* parameter was set to $C = 1$.

3.7 Parameters of Neural Network Classifier

The *Neural Network* toolbox produces different CA based on its *Neurons in hidden layers*, *Activation*, and *Solver* parameters. In our work, this classifier was implemented as an MLP of 2 hidden layers, due to the MLP architecture of more hidden layers had the same generated CA with the same parameters selection. The following activation functions of *Logistic*, *tanh*, and *ReLU* [41] as well as the solver optimizers of *SGD* [42] and *Adam* [43] were selected in this work, due to their robustness and non-linearity behaviors. Note that the *Regularization* parameter was set to 0.9 and the *Maximal number of iterations* was set to 100. Table 3 states the generated CA based on these three parameters.

The best-chosen CA was 91.0% for the MLP architecture of the (100 × 100 × 4) neurons with ReLU activation and Adam solver parameters selection, as well as of the (500 × 500 × 4) neurons with tanh activation and Adam solver parameters selection. However, the small MLP architecture of (100 × 100 × 4) neurons was chosen due to its fewer number of the utilized neurons that decrease the classification time, rather than the medium MLP architecture of (500 × 500 × 4) neurons.

4 Results and Discussion

In our work, the obtained human-classifiable results were based on the following factors: (1) the number of medical samples in the training and test datasets, (2) the seven proposed machine learning classifiers, (3) the selected and tuned parameters for each classifier, and (4) the predicted probabilities. Moreover, the *Predictions* toolbox was implemented to visually illustrate the predicted probabilities for the test dataset based on their labels as well as the outcome signals from the classifiers based on the training dataset. These predicted probabilities are CA, AUC (Area under ROC—Receiver Operating Characteristic), Precision, Recall, and F1 (a weighted harmonic mean of Precision and Recall) that used to compute the statistical performance of a machine learning classifier [44], as demonstrated in Fig. 14. Note that, in this

Table 3 CA based on Neurons in hidden layers, Activation, and Solver parameters

Activation/solver	Neurons in hidden layers (%)		
	100 × 100 × 4	500 × 500 × 4	1000 × 1000 × 4
Logistic/SGD	57.3	57.3	57.3
Logistic/Adam	57.3	57.3	57.3
tanh/SGD	78.7	88.8	86.5
tanh/Adam	85.9	91.0	85.4
ReLU/SGD	67.4	85.4	77.5
ReLU/Adam	91.0	79.8	65.2

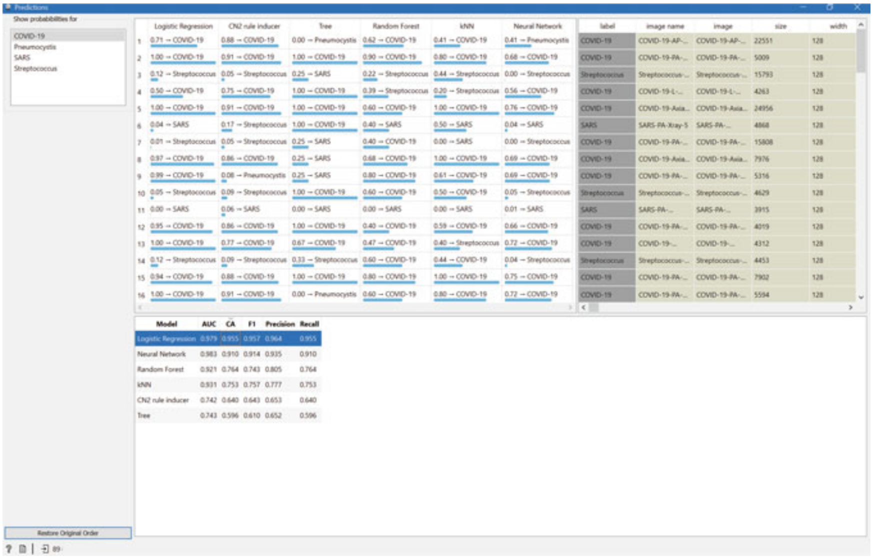


Fig. 14 Orange Predictions toolbox, (top) the blue bars show the strength of each classifier in predicting the four infected cases individually or as a group, and (bottom) the predicted probabilities (CA, AUC, Precision, Recall, and F1) of computing the statistical performance for each classifier

Predictions toolbox, the cases can be chosen individually or as a group to show the best-chosen classifier(s) that predicted them, as denoted by the lengths, or *strengths*, of the blue bars.

Moreover, other Orange toolboxes, such as *Confusion Matrix, Linear Projection*, and *Sieve Diagram*, were implemented to calculate the correlations and illustrate the projections between the training dataset and the test dataset for each machine learning classifier.

4.1 Results from Confusion Matrix

Figure 15 illustrates the correlation between the actual and the predicted cases on the samples from the test dataset as comparable matrices for each classifier regarding the four infected cases. It was observed that the COVID-19 samples were more classifiable under the Logistic Regression and Neural Network than the other classifiers, and especially for the Logistic Regression classifier since it has only four mismatched COVID-19 cases with Streptococcus cases, then followed by the Neural Network classifier that has eight mismatched COVID-19 cases with Pneumocystis and Streptococcus cases.

Predicted

Actual	COVID-19	Pneumocystis	SARS	Streptococcus	Σ
COVID-19	47	0	0	4	51
Pneumocystis	0	12	0	0	12
SARS	0	0	10	0	10
Streptococcus	0	0	0	16	16
Σ	47	12	10	20	89

Logistic Regression Classifier

Predicted

Actual	COVID-19	Pneumocystis	SARS	Streptococcus	Σ
COVID-19	37	8	2	4	51
Pneumocystis	5	4	0	3	12
SARS	3	0	5	2	10
Streptococcus	4	1	0	11	16
Σ	49	13	7	20	89

CN2 Rule Induction Classifier

Predicted

Actual	COVID-19	Pneumocystis	SARS	Streptococcus	Σ
COVID-19	30	10	9	2	51
Pneumocystis	2	8	0	2	12
SARS	4	0	5	1	10
Streptococcus	3	2	1	10	16
Σ	39	20	15	15	89

Tree Classifier

Predicted

Actual	COVID-19	Pneumocystis	SARS	Streptococcus	Σ
COVID-19	49	0	0	2	51
Pneumocystis	7	5	0	0	12
SARS	5	0	4	1	10
Streptococcus	6	0	0	10	16
Σ	67	5	4	13	89

Random Forest Classifier

Predicted

Actual	COVID-19	Pneumocystis	SARS	Streptococcus	Σ
COVID-19	38	1	3	9	51
Pneumocystis	3	8	0	1	12
SARS	2	0	8	0	10
Streptococcus	3	0	0	13	16
Σ	46	9	11	23	89

kNN Classifier

Predicted

Actual	COVID-19	Pneumocystis	SARS	Streptococcus	Σ
COVID-19	43	6	0	2	51
Pneumocystis	0	12	0	0	12
SARS	0	0	10	0	10
Streptococcus	0	0	0	16	16
Σ	43	18	10	18	89

Neural Network Classifier

Fig. 15 Confusion matrices for each classifier, and the Logistic Regression classifier performs well on COVID-19 cases classification

4.2 Results from Linear Projection

As demonstrated in Fig. 16, the COVID-19 samples, as the blue dots, were selected to be linearly projected with the Logistic Regression, Tree, Random Forest, kNN, and Neural Network classifiers to check their accurate classification and performance. It was visually noted that the COVID-19 samples were more classifiable under the Logistic Regression and Neural Network than the other classifiers, and especially for the Logistic Regression classifier due to a large number of blue dots around its axis, then followed by the Neural Network classifier.

4.3 Results from Sieve Diagram

Orange *Sieve Diagram* toolbox provides the N samples visualization of the test dataset along with a pair of classifiers, as well as shows the *Sieve Rank* (X^2). The darker blue regions are the stronger is the relationship of a given case for a pair of classifiers. This can be influenced on the X^2 as well, so that the higher X^2 gives a better illustration of the stronger relationship for a given case among a pair of classifiers.

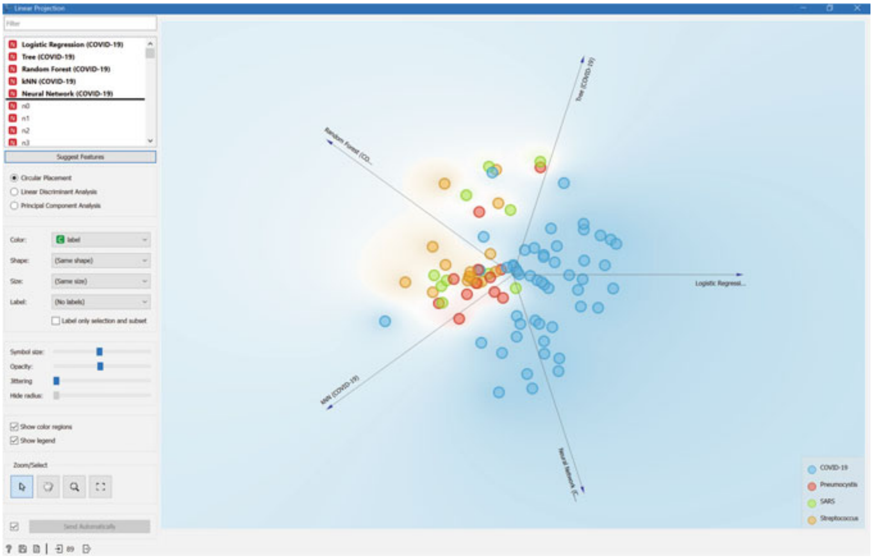


Fig. 16 Linear projection of COVID-19 samples, as the blue dots, within the five classifiers, and the Logistic Regression classifier performs well on COVID-19 cases classification

Figure 17 shows different Sieve diagrams for different pairs of classifiers, and it was visually observed that the COVID-19 samples were more classifiable under the pair of Logistic Regression and Neural Network classifiers. This observation was based on darker blue regions and higher X^2 than for other pairs of classifiers. On the other hand, the COVID-19 samples were less classifiable under the pairs of Logistic Regression and Tree/Random Forest/CN2 Rule Inducer classifiers, which have lighter blue regions and lower X^2.

5 Conclusions

When more medical images regarding the COVID-19 datasets have been clinically provided and publicly available, this will open the chance to do more research in this field as well as increase the number of samples to the classifiers, which yields to get better modeling performance and classification accuracy. Hence, larger datasets of various diseases' cases will contribute to do more labeling assignments, however less data augmentation would be required. The image scaling of 128 × 128 pixels was chosen, in this work, for the purpose of fast processing time, but this downscaling may also affect the hidden features of these diagnostic images, which gives at the end no better features extraction and detection using the Orange Inception v3 model toolbox. Our work was implemented using Orange software, a visual analytical tool for epidemiology specialists that have little knowledge in machine learning

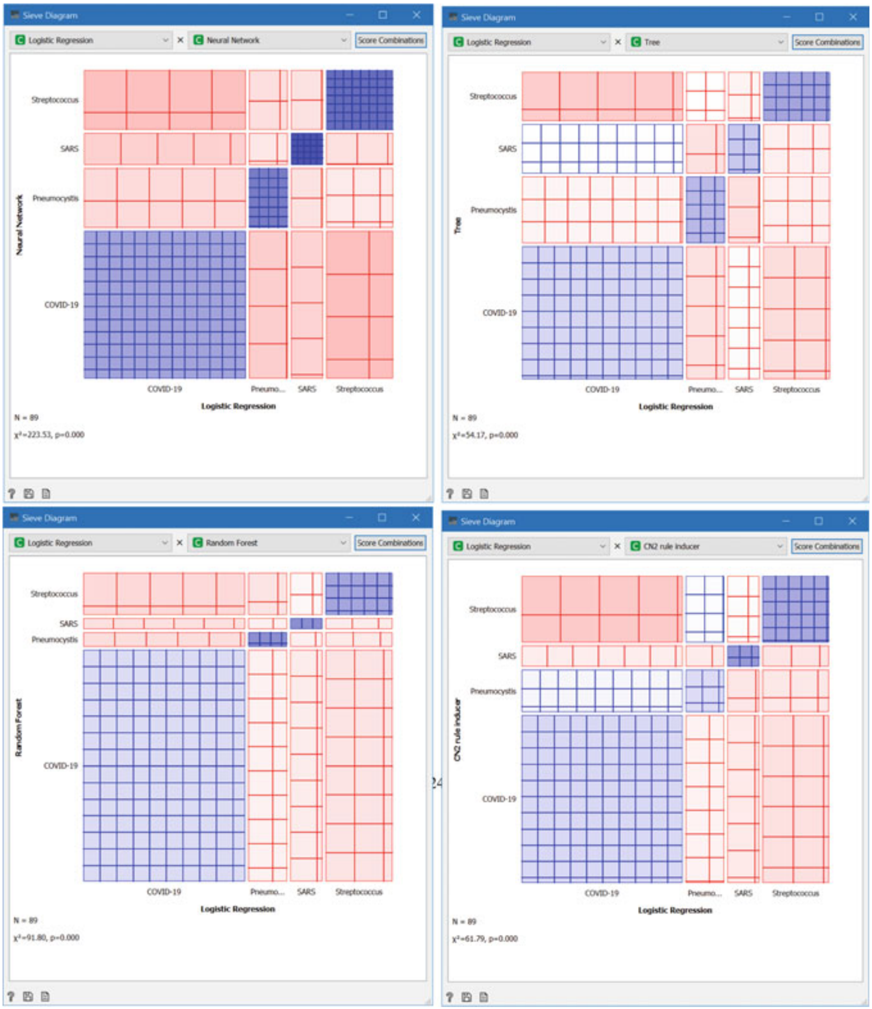


Fig. 17 Sieve diagrams for pairs of classifiers, N is the number of test samples and X^2 is Sieve rank. (top-left) the pair of Logistic Regression and Neural Network classifiers performs well on COVID-19 cases classification with darker blue regions and higher X^2

techniques and limited programming skills, to allow them to focus on COVID-19 cases analysis and classification with ease of use and simplicity of understanding and manipulating.

Some of the toolboxes' parameters do not affect the overall workflow, while others do. Table 4 describes the parameters that have been carefully chosen for better rules, easy visualization, as well as higher performance and CA.

Based on Table 4, the *Predictions* toolbox demonstrates different CA for different classifiers. The higher CA is, the better classifier does, as categorized by Table 5.

Table 4 Parameters selection for higher performance and CA

Toolbox	Parameter(s)	Setting
Distances	Distance metric	Cosine
CN2 Rule induction	Evaluation measure	Laplace accuracy
Tree	Min. number of instances in leaves	3
Random forest	Number of trees	10
kNN	Number of neighbors	5
	Weight	Distance
Logistic regression	Regularization type	Ridge (L2)
Neural network	Neurons in hidden layers	$100 \times 100 \times 4$
	Activation	ReLU
	Solver	Adam

Table 5 CA ranking for each classifier

Classifier	CA (%)
Logistic regression	95.5
Neural network	91.0
Random forest	76.4
kNN	75.3
CN2 rule induction	64.0
Tree	59.6

Based on the *Confusion Matrix* toolbox, as in Fig. 15 shown previously, the Logistic Regression classifier has a better matching between the actual and the predicted cases for the samples from the test dataset, and then followed by the Neural Network classifier. While the Tree classifier has the worst matching pattern. Therefore, this is in agreement with Table 5. Based on the *Linear Projection* toolbox, as in Fig. 16 shown previously, the Logistic Regression and Neural Network classifiers have the most COVID-19 cases projection along their axes than the other classifiers. Therefore, this is in agreement with Table 5.

Based on the *Sieve Diagram* toolbox, as in Fig. 17 shown previously, the pair of Logistic Regression and Neural Network classifiers have the most test samples frequencies of COVID-19 cases, due to the darker blue regions and higher X^2. Therefore, this is in agreement with Table 5. Based on the careful parameters selection and tuning for each classifier, the *Predictions* toolbox, the *Confusion Matrix* toolbox, the *Linear Projection* toolbox, the *Sieve Diagram* toolbox, and the CA from Table 5, the Logistic Regression model was the appropriate best-chosen classifier in identifying and classifying the COVID-19 cases among the other similar human-being lungs infected cases (SARS, Pneumocystis, and Streptococcus). The achieved CA for the Logistic Regression classifier was up to 95.5%. Figure 18 demonstrates the completed

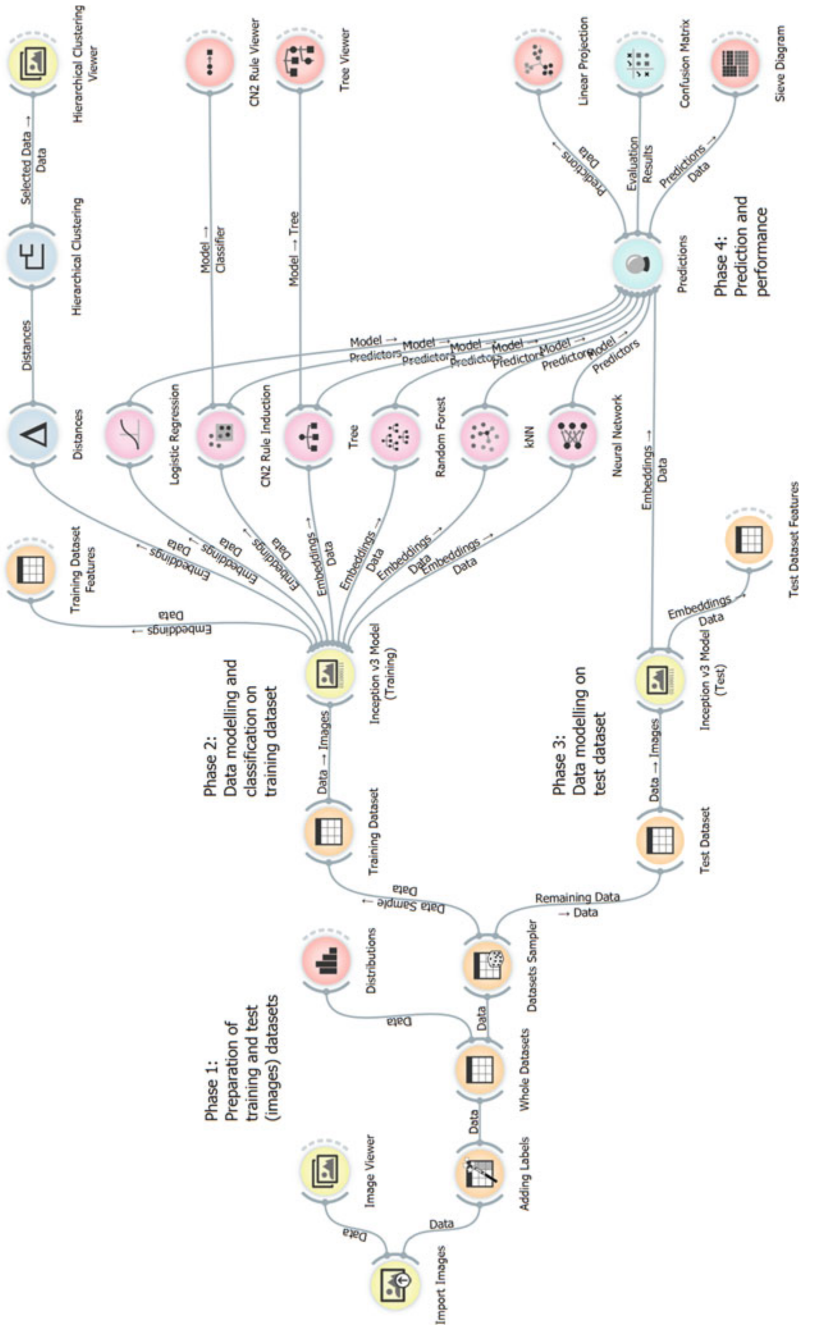


Fig. 18 Orange phases, toolboxes, and signals workflow layout

layout of all connected phases, toolboxes, and signals to achieve the overall Orange workflow for COVID-19 features detection and extraction using machine learning classifiers.

References

1. World Health Organization. Coronavirus disease (COVID-19) pandemic. WHO.int. https://www.who.int/emergencies/diseases/novel-coronavirus-2019. Accessed 4 May 2021
2. Marmanis, D., Datcu, M., Esch, T., Stilla, U.: Deep learning earth observation classification using ImageNet pretrained networks. IEEE Geosci. Remote Sens. Lett. **13**(1), 105–109 (2015)
3. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. Adv. Neural. Inf. Process. Syst. **25**, 1097–1105 (2012)
4. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., Lungren, M.P.: CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning (2017). arXiv preprint arXiv:1711.05225
5. Ayan, E., Ünver, H.M.: Diagnosis of pneumonia from chest X-ray images using deep learning. In: 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT) pp. 1–5
6. Stephen, O., Sain, M., Maduh, U.J., Jeong, D.U.: An efficient deep learning approach to Pneumonia classification in healthcare. J. Healthc. Eng. (2019). https://doi.org/10.1155/4180949
7. Alimadadi, A., Aryal, S., Manandhar, I., Munroe, P.B., Joe, B., Cheng, X.: Artificial intelligence and machine learning to fight COVID-19. Physiol. Genomics **52**, 200–202 (2020). https://doi.org/10.1152/00029.2020
8. Pinter, G., Felde, I., Mosavi, A., Ghamisi, P., Gloaguen, R.: COVID-19 pandemic prediction for Hungary; a hybrid machine learning approach. Mathematics **8**(6) (2020). https://doi.org/10.3390/math8060890
9. Elaziz, M.A., Hosny, K.M., Salah, A., Darwish, M.M., Lu, S., Sahlol, A.T.: New machine learning method for image-based diagnosis of COVID-19. PLOS ONE **15**(6) (2020). https://doi.org/10.1371/journal.pone.0235187
10. Sujath, R., Chatterjee, J.M., Hassanien, A.E.: A machine learning forecasting model for COVID-19 pandemic in India. Stoch. Env. Res. Risk Assess. **34**, 959–972 (2020). https://doi.org/10.1007/s00477-020-01827-8
11. Ardabili, S.F., Mosavi, A., Ghamisi, P., Ferdinand, F., Varkonyi-Koczy, A.R., Reuter, U., Rabczuk, T., Atkinson, P.M.: COVID-19 outbreak prediction with machine learning. Algorithms **13**(10) (2020). https://doi.org/10.3390/a13100249
12. Brinati, D., Campagner, A., Ferrari, D., Locatelli, M., Banfi, G., Cabitza, F.: Detection of COVID-19 infection from routine blood exams with machine learning: a feasibility study. J. Med. Syst. **44**(135), 1–12 (2020). https://doi.org/10.1007/s10916-020-01597-4
13. Cheng, F.Y., Joshi, H., Tandon, P., Freeman, R., Reich, D.L., Mazumdar, M., Kohli-Seth, R., Levin, M., Timsina, P., Kia, A.: Using machine learning to predict ICU transfer in hospitalized COVID-19 patients. J. Clin. Med. **9**(6) (2020). https://doi.org/10.3390/jcm9061668
14. Rustam, F., Reshi, A.A., Mehmood, A., Ullah, S., On, B.W., Aslam, W., Choi, G.S.: COVID-19 future forecasting using supervised machine learning models. IEEE Access **8**, 101489–101499 (2020). https://doi.org/10.1109/ACCESS.2020.2997311
15. Kumar, S.R.: Novel Corona Virus 2019 Dataset V151. Distributed by Kaggle Inc. https://www.kaggle.com/sudalairajkumar/novel-corona-virus-2019-dataset
16. Allen Institute for AI: COVID-19 Open Research Dataset Challenge (CORD-19) V92. Distributed by Kaggle Inc. https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge

17. Orange: University of Ljubljana (2021). Accessed Apr 2021. https://orangedatamining.com
18. Gärtner, T., Lloyd, J.W., Flach, P.A.: Kernels and distances for structured data. Mach. Learn. **57**(3), 205–232 (2004)
19. Collins, M., Schapire, R.E., Singer, Y.: Logistic regression, AdaBoost and Bregman distances. Mach. Learn. **48**(1), 253–285 (2002)
20. Dreiseitl, S., Ohno-Machado, L.: Logistic regression and artificial neural network classification models: a methodology review. J. Biomed. Inform. **35**, 352–359 (2002)
21. Clark, P., Boswell, R.: Rule induction with CN2: some recent improvements. In: Machine Learning—Proceedings of the Fifth European Conference (EWSL-91), pp. 151–163 (1991)
22. Džeroski, S., Grbovic, J., Walley, W.J., Kompare, B.: Using machine learning techniques in the construction of models. II. Data analysis with rule induction. Ecol. Model. **95**(1), 95–111 (1997)
23. Dietterich, T.G., Kong, E.B.: Machine learning bias, statistical bias, and statistical variance of decision tree algorithms pp. 0–13. Technical report, Dept. of Computer Science, Oregon State University, USA (1995)
24. Olson, R.S., Moore, J.H.: TPOT: A tree-based pipeline optimization tool for automating machine learning. In: Workshop on Automatic Machine Learning (ICML), pp. 66–74 (2016)
25. Segal M.R.: Machine learning benchmarks and random forest regression. UCSF: Center for Bioinformatics and Molecular Biostatistics (2004). Retrieved from https://escholarship.org/uc/item/35x3v9t4
26. Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., Chica-Rivas, M.: Machine learning predictive models for mineral prospectivity: an evaluation of neural networks, random forest, regression trees and support vector machines. Ore Geol. Rev. **71**, 804–818 (2015). https://doi.org/10.1016/j.oregeorev.2015.01.001
27. Kramer, O.: K-nearest neighbors. In: Dimensionality Reduction with Unsupervised Nearest Neighbors. Intell. Syst. Ref. Libr. **51**, 13–23 (2013). https://doi.org/10.1007/978-3-642-38652-7_2
28. Zhang, Z.: Introduction to machine learning: k-nearest neighbors. Ann. Transl. Med. **4**(11) (2016). https://doi.org/10.21037/atm.2016.03.37
29. Chen, H.: Machine learning for information retrieval: Neural networks, symbolic learning, and genetic algorithms. J. Am. Soc. Inf. Sci. **46**(3), 194–216 (1995)
30. Lampignano, J.P., Kendrick, L.E.: Bontrager's Handbook of Radiographic Positioning and Techniques, 9th edn. Mosby, USA (2017)
31. Herring, W.: Learning Radiology: Recognizing the Basics, 4th edn. Elsevier, USA (2019)
32. Abu-Mostafa, Y.S., Magdon-Ismail, M., Lin, H.T.: Learning From Data: A Short Course. AMLBook, USA (2012)
33. ACDSee: ACD Systems International Inc. (2020). https://www.acdsee.com
34. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z.: Rethinking the inception architecture for computer vision. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 2818–2826
35. Deng, X., Liu, Q., Deng, Y., Mahadevan, S.: An improved method to construct basic probability assignment based on the confusion matrix for classification problem. Inf. Sci. **340**, 250–261 (2016). https://doi.org/10.1016/j.ins.2016.01.033
36. Hidayatullah, R.S., Cholifah, W.N., Ambarsari, E.W., Kustian, N., Julaeha, S.: Sieve diagram for data exploration of Instagram usage habit obtained from Indonesia questioner's sample. J. Phys. **1783**(1) (2021). https://doi.org/10.1088/1742-6596/1783/1/012028
37. Belhumeur, P.N., Hespanha, J.P., Kriegman, D.J.: Eigenfaces vs. fisherfaces: recognition using class specific linear projection. IEEE Trans. Pattern Anal. Mach. Intell. **19**(7), 711–720 (1997). https://doi.org/10.1109/34.598228
38. MacKay, D.: Information Theory, Inference and Learning Algorithms, 1st edn. Cambridge University Press, UK (2003)
39. Martínez-Martínez, J.M., Escandell-Montero, P., Soria-Olivas, E., Martín-Guerrero, J.D., Magdalena-Benedito, R., GóMez-Sanchis, J.: Regularized extreme learning machine for regression problems. Neurocomputing **74**(17), 3716–3721 (2011). https://doi.org/10.1016/j.neucom.2011.06.013

40. Tibshirani, R.: Regression shrinkage and selection via the lasso. J. Roy. Stat. Soc. **58**(1), 267–288 (1996)
41. Zhang, H., Weng, T.W., Chen, P.Y., Hsieh, C.J., Daniel, L.: Efficient neural network robustness certification with general activation functions (2018). arXiv preprint arXiv:1811.00866
42. Qian, N.: On the momentum term in gradient descent learning algorithms. Neural Netw. **12**(1), 145–151 (1999). https://doi.org/10.1016/S0893-6080(98)00116-6
43. Kingma, D.P., Ba, J.: Adam: a method for stochastic optimization (2017). arXiv preprint arXiv:1412.6980
44. Powers, D.M.W.: Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. 2020, arXiv preprint arXiv:2010.16061

Cough Detection Using Mobile Phone Accelerometer and Machine Learning Techniques

Shan E. Ali, Ali Nawaz Khan, and Shafaq Zia

Abstract Timely cough diagnosis is important due to prevalence of severe upper respiratory tract infection during COVID-19 pandemic. Cough monitoring can aid in the detection of onset of severe infections. With a variety of embedded sensors, increased memory, higher processing capabilities, and widespread availability; smartphones can be employed to detect coughs by actively monitoring the movements of chest muscles. This chapter describes a three-axis accelerometer-based approach for detecting and classifying cough occurrences in human subjects through application of machine learning algorithms to movement data. In an unconstrained environment, movement data is captured in real-time from the embedded accelerometer of a smartphone carried by subject in upper-left pocket of shirt. Preprocessing of data is done with noise reduction, standardization, and data re-sampling techniques to ensure efficient model training. Supervised machine learning approaches are utilized to classify cough into three categories of mild, chronic and breathing episodes depending upon intensity of movement in chest muscles. According to the collected data and comparative examination of training models, Random Forest surpassed other algorithms with an accuracy of 89.1% and high precision corresponding to 19,000 samples of training data. Proposed system classifies activities from movement data stored in the cloud instead of performing this task within mobile phone application to accommodate a host of users using smartphones with varying software and hardware specifications for assisted living applications.

Keywords Cough detection · Cough monitoring · Human movement data · COVID-19 biomarkers · Machine learning for healthcare applications

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1 Introduction

Worldwide COVID-19 pandemic has imposed immense challenges on healthcare system and exposed weakest points and problems of the traditional diagnostic practices. As healthcare systems are trying to cope with the rapid and enormous demands for testing patients, novel ways for diagnosis, monitoring and managing patients are also essential to combat the pandemic.

1.1 Cough an Important Biomarker for COVID-19 Identification

There are several symptoms or biomarkers for the detection of COVID-19 infection and prevalence in human subjects. World Health Organization (WHO) and Centers for Disease Control and Prevention (CDC) have identified dry cough, breathing difficulties, chest pain and fatigue as the most important symptoms of viral infection during the first wave of COVID-19. These symptoms could be seen between 2 and 14 days after exposure. One of the important biomarkers is cough. It has distinguishing characteristics to it which can help in identifying the onset and severity of disease.

1.2 Overview of Cough

Cough is a natural defense mechanism to propel unwanted elements out of human respiratory tract. When we cough, a complex physiologic response is activated to protect airways from unwanted secretions or foreign objects. It alleviates obstructions in the respiratory stream. We can classify coughs as wet or dry coughs, based on their acoustic quality sound. The cough pattern has three distinct phases. These three different phases are inspiratory phase, compressive phase, and expulsive phase. Both inspiratory and expiratory muscles are actively involved during coughs. Extreme changes in intrapleural pressure occur because of active contraction of these muscles. Repeated coughs can cause multiple complications such as rupture, lung herniation through the intercostal space, and rib fracture. Details of cough types, patterns, and muscular movement are discussed in literature review.

1.3 Levels of Cough Severity

We can classify cough as acute, subacute, or chronic based on duration. Acute coughs subside in three weeks, while subacute coughs last longer than three weeks and up to eight weeks. Chronic cough refers to serious infections that last longer than eight weeks [1].

Mild or subacute cough is most often caused by upper respiratory tract infections (URTIs) or viral infections. Intensity of this cough is lower than chronic cough. Determining the intensity of cough is also important along with duration for correct diagnosis.

1.4 Common Respiratory Diseases

Table 1 presents a list of common respiratory diseases, their prevalence among the worldwide population, and key biomarkers, along with other characteristics [2].

World population is 7.9 billion in 2021. More than a billion persons, that is 12.29% of world population, suffer from respiratory diseases. Asthma accounts for 23.5%, COPD has 20%, TB is prevalent among 11% and 5% of all respiratory cases are due to pneumonia. Lung cancer is the leading cause of death with more than 40% of total deaths due to respiratory disorders [5].

Table 1 Prevalence of respiratory diseases and key biomarkers

Respiratory diseases	Disease prevalence (%)	Symptoms	Cough duration	Cough frequency	Cough type
COVID-19	17	Cough, fever, fatigue	Short/long	High	Dry
Asthma	23.5	Cough, wheeze, chest tightness, abnormal breathing	Short	Low 100–900 Hz	Wet
Tuberculosis (TB) [3]	11	Cough, chest sore, fatigue	Long	High 1 kHz	Wet
Pneumonia [4]	5	Cough, fever, abnormal breathing, fatigue	Long	Low 476 Hz	Wet
COPD [4]	20	Cough, wheeze, shortness of breath	Long	Low—412 Hz	Wet

1.5 Different Cough Conditions

Although the occurrence of cough is common in medical respiratory conditions, its presence in non-respiratory and environmental conditions is also evident.

Cough is a common symptom of most medical respiratory conditions. The reason for a respiratory medical condition is common respiratory diseases. Gastroesophageal reflux disease, heart failure, and tumors are examples of non-respiratory medical conditions. A variety of environmental factors can also trigger coughing, including cooking fumes, smoking, and air pollution. But this is a transient state that lasts until the environmental conditions return to normal.

Having identified that cough is a valid biomarker for identifying prevalence and onset of COVID-19, in this chapter, we investigate workable methods for automatic detection and classification of cough for long-term activity monitoring and identification of patients. An early diagnostic tool in the form of mobile phone application may help masses identify the severity of the disease. It can also be used to indicate the need and urgency for hospitalization. Such a mobile application may also enable tracking of patients to limit the spread of disease. The mobile app may be linked to database servers accessed by government agencies and healthcare professionals to devise a better strategy for restricting the spread of infection in a complete healthcare solution.

The rest of the chapter is organized as follows. Section 2 shows the background related to cough detection techniques, discussion of related work with available machine learning techniques as a solution to the task at hand. Section 3 presents the research methodology as data collection, data preprocessing, and implementation of machine learning techniques used in the cough detection system. Section 4 shows results evaluated by applying a machine learning algorithm to collected data. Finally, the conclusions and future work are discussed in Sect. 5.

2 Literature Review

Studies about cough detection methodologies, key biomarkers and machine learning techniques are presented in this section.

2.1 Cough Occurrence, Types and Patterns

Cough is an effective reflex mechanism for clearing inhaled and secreted material from the central airways (trachea and main stem bronchi). It follows a well-defined pattern, beginning with inspiration, glottal closure, and the development of increased thoracic pressure, followed by an explosive expiratory flow as the glottis opens in response to continued expiratory effort [6]. Air turbulence, tissue vibration, and the

Table 2 Common COVID-19 symptoms

Ref	Source	Common symptoms
[2]	W.H.O	Fever, cough, abnormal breathing
[10]	WebMD	Cough, fever
[11]	MayoClinic	Cough, tiredness, fever
[12]	CDC	Fever, fatigue, cough

flow of fluid through the airways are responsible for the sound and muscle reflex produced by coughing. Coughs are categorized into types, patterns, and duration based on the presence of liquid, airway channels, and duration of the cough [7].

Coughs can be classified as wet or dry coughs, based on their acoustic quality sound. Wet cough occurs as a result of the disturbance and occasionally as a result of secretions such as mucus and pus. Inflammations that produce no fluid secretions cause dry coughs [8]. Because of the underlying disease that causes cough, the cough may comprise of only two phases: intermediary and voiced. An intermediatory phase of the cough causes pectoral muscles to contract and expand. This leads to abrupt movements of the torso and chest. Medical literature shows that speech breathing patterns are intricately tied to changes in anatomy and physiology of the respiratory system [9].

2.2 Cough Is a Valid Indication of COVID-19 Disease

Symptoms of COVID-19 range from mild fever to loss of taste and smell; it is a broad category and could differ in various ways depending upon health condition of a person. However, there is a list of key symptoms listed by various health organizations across the globe. On top of that list are fever and cough symptoms worldwide. These symptoms can be divided into conventional and unconventional symptoms. Conventional Symptoms are the ones that are considered to be common in most types of viral infections such as fever, shortness of breath, fatigue. Unconventional symptoms are the ones that occur in a particular type of infection such as cough, sneezing and flu.

Table 2 presents the most common symptoms of COVID-19 according to sources such as W.H.O, WebMD, MayoClinic and CDC. Cough and fever are the frequently mentioned symptoms in all sources. In addition to that tiredness, chronic fatigue and abnormal breathing were also reported.

2.3 Severity of Cough Indicates the Prevalence of Disease

A study [13] observed 600 randomly selected COVID-19 patients to examine the onset of symptoms and progression of the disease. Among 128 hospitalized patients,

Table 3 Patient types and symptom prevalence

Type of patients	Number of patients	Key symptoms	Study
Hospitalized patients	128	Fever, cough, physical exhaustion	[13]
Non-hospitalized patients	238	Fatigue, fever, cough	[14]
Both	327	Lower respiratory tract infection, cough, fever	
Healthcare staff	48	Fever, cough	[15]

along with fever and exhaustion, cough was the most frequently reported symptom (73%). Among 236 non hospitalized patients, fatigue (90%), fever (8%), and cough were the most often reported symptoms (83%), General and upper respiratory symptoms begin sooner in the disease's course. Later, patients also developed symptoms of the lower respiratory tract. So, the most frequently reported symptoms of COVID-19 were fever and cough [14].

91% of hospitalized patients and 90% of non-hospitalized patients reported symptoms consistent with a possible lower respiratory tract infection (cough, wheezing, or chest pain). Fever, cough, and weariness were the most often reported symptoms among hospitalized patients. Cough and fever were the most often reported early symptoms in COVID-19 patients. These were also the most often reported initial symptoms by 48 healthcare staff infected with COVID-19 in King County, Washington state [15].

Duration and progression of COVID-19 symptoms are investigated in [16]. Fever is the most often reported symptom, followed by a cough. For a few days, as the condition advanced, the cough became more chronic. We are not recommending the initial symptom as a diagnostic test, but as a sign to seek medical attention. COVID-19 outbreaks occur in clusters, and these atypical clusters of disease indicate a pandemic disease that requires prompt attention with vigorous testing to halt spread [17].

It is important to follow up with COVID-19 patients, as severity in any common symptoms shows the severity of disease and may point towards hospitalization of the patient [18]. To improve recognition of coronavirus disease (COVID-19) and to inform clinical and public health guidance. Table 3 summarizes the patients and key symptoms observed most frequently among those cases.

Figure 1 illustrates the percentage prevalence of common COVID-19 symptoms of and Fig. 2 illustrates different patient types of COVID-19.

2.4 Cough Represents the Severity of Disease

Cough can be recorded through microphones for analysis and classification. Several features have been presented in the literature to define the properties of a speech signal containing cough in both time and frequency domains. An essential consideration is

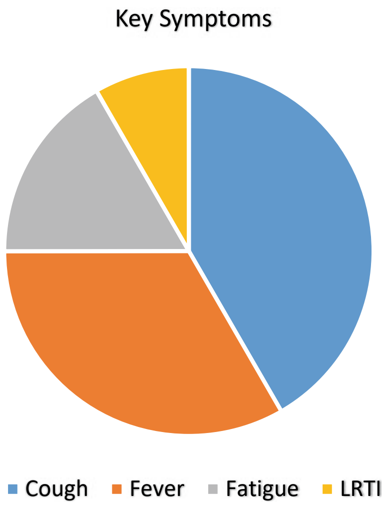

Fig. 1 Percentage of common key symptoms of COVID-19

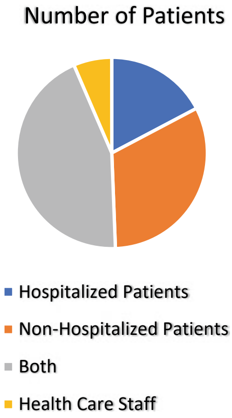

Fig. 2 Percentage of different COVID-19 patients types

extraction of variety of features, from which only the most important will be chosen [19].

Before collecting information from the cough signal, it is required to preprocess the audio data to remove sources of noise that obstruct its evaluation. In general, cough occurrences are segmented and isolated from sources of noise using noise removal techniques. Methods for noise removal are performed either manually or automatically. Automated noise removal methods include standard deviation, short-term energy, and zero-crossing [20].

A common feature of cough detection has been the Mel-frequency cepstral coefficients (MFCC) and their modifications. The MFCC coefficients, employed in automatic speech recognition, represent the envelope of a speech signal's short-term power spectrum. Additionally, spectral shape characteristics may aid in distinguishing cough from other sounds, notably speech. As in comparison to speech, cough sounds are more akin to noise, and hence have a broader spectrum [21].

To date, cough detection algorithms have utilized a variety of unique spectral properties. Spectral flatness indicates how close a signal's spectrum is to noise; spectral centroid shows the spectrum's weighted mean, which is greater in cough sounds. Formant frequencies indicate spectral peaks at the cough-generating resonant frequencies and spectral kurtosis shows the spectrum's peak [22]. Cough noises are more prone to noise than other sounds, and thus more complicated. As a result, alternative metrics of the complexity of cough sound signals, such as zero-crossing rate [23] or different entropy measurements have been proposed for cough detection [24].

Other attributes have also been used to detect coughs. These include the non-Gaussianity score [25], which quantifies signal deviation from a Gaussian model and is quite high in cough sounds; log-energy, which is related to the amplitude of cough signals; and Hu moments, a technique of weighted averaging used in image processing and proposed in the signal processing field for speech emotion. Typically, these and additional characteristics are integrated to create the categorization input data set. However, no consensus exists on the optimal set of auditory characteristics for cough recognition [26, 27]. Most of these feature extraction methods and techniques are proposed and evaluated for auditory analysis. Above mentioned pre-processing techniques are summarized in Table 4.

Table 4 Several pre-processing techniques for cough signal analysis

Techniques	Characteristic	Application
Time domain	Standard deviation	Noise removal
	Short-term energy	Pre-processing
	Zero-crossing	Pre-processing
	Entropy measurements	Pre-processing
Frequency domain	MFCC	Speech recognition
	Spectral shape	Auditory analysis
	Spectral centroid	Auditory analysis
	Spectral peak	Auditory analysis
Others	Non-Gaussinity score	Auditory analysis
	Hu moments	Image processing
	Log energy	

2.5 *Existing Methods for Cough Detection*

To detect the prevalence or presence of cough in a patient, the literature review is divided into two broad categories of acoustic or sound based approaches and wearable sensor based approaches. We will discuss these approaches and their limitations below.

2.5.1 Sound Based Approaches

Coughing is a common symptom of most respiratory diseases. While cough sounds can be useful in diagnosing some diseases, their strength and frequency also indicate the severity of the sickness. Here we are discussing various approaches for cough detection, their limitations and the work done to overcome these limitations.

The study of [28] stated that a powerful method for identifying and analyzing cough sounds is critical for the success of a system. Researchers face technical challenges when implementing such systems, including the choice of sensors and signal acquisition methods, real-time analysis of acquired signals, and precise detection of cough occurrences, differentiating cough sound from similar sounds such as speaking, laughing, throat clearing, and snoring. The majority of past research on cough detection has taken a conventional approach to acoustic signal processing, employing techniques from automatic speech recognition. These steps include the essence of strategy: silence elimination, feature extraction, and categorization. However, several approaches to these processes have been proposed, and there is currently no defined methodology for automatic cough identification [29].

The most extensively researched signal for cough evaluation is sound, which is obtained by microphones. Microphones are split into two types: contact and noncontact. Non-contact microphones are worn on the subject's outer clothing or situated close to the subject and detect changes in air pressure that are translated to electrical impulses via transduction. Contact microphones are connected to the skin's surface and detect audio vibrations via piezoelectric transducers. While they are less susceptible to ambient noise than noncontact microphones, high sensitivity makes them susceptible to noise caused by movement disturbances.

A sampling frequency range of 8 to 48 kHz has been suggested for the collection of the sound. The microphone's frequency response must be within the range of the coughing occurrences. Additionally, the sampling rate must consider the cough noises' highest frequency component; according to the Nyquist sampling theorem, elements greater than half the sample rate must be filtered away to avoid aliasing. The sample rate affects the amount of data obtained; lower rates minimize equipment and data storage needs, as well as the time required to do automated analysis, all of which are critical for developing practical applications [30].

Larson's study also emphasizes a challenge that most acoustic sensing systems encounter: privacy and security. Because of the microphone's ability to pick up on speech and other audio signals, methods for registering only cough signals are required to avoid invading the patient's speech privacy. Wireless transmission of such data to a server or substation requires specific security measures to safeguard patient health information [31].

These difficulties may be overcome by decomposing acoustic signals into matrices of eigenvectors and then communicating only the eigenvectors to the server. Collected cough data is reassembled for further processing on other server-side. Segmentation and reconstruction are carried out in such a way that only cough data can be reliably recreated. While this technique is encouraging, it does not ensure the privacy of other types of audio information, such as the user's identity or location. As a result, privacy and security remain significant concerns while designing cough monitoring systems [28].

2.5.2 Wearable Sensors Approach

Several studies attempted cough recognition using various wearables sensors and devices. In [32], a proof-of-concept non-contact system for measuring capacitive electrocardiogram (cECG) and cough-associated capacitive electromyogram (cEMG) using cloth electrodes concealed beneath a pillowcase is presented. All subjects had visible cEMGs for each cough motion, which were synchronized with reference EMGs from submental muscle. Although there is still room for improvement in practical application, it was performed under a constrained environment and the article focused on detection of cough for diagnosing pulmonary diseases and asthma.

The miniaturization of electronic devices and the digitalization of recording technology have resulted in the development of wearable cough monitors that can perform much more efficiently as compared to devices developed a decade ago. There have been several recent attempts to develop automated or semiautomated cough frequency monitors. However, few systems have been widely adopted in cough research, such as VitaloJAKTM [33]. Some other systems also gained attention, such as AI4COVID-19 [34] which is an Artificial Intelligence (AI) system that uses a novel multipronged mediator-centered risk averse architecture to recognize COVID-19 initial symptoms. FluSense [35] is using an edge computing technique that enables crowd behavior and influenza monitoring using cough as an indicator.

A non-invasive pneumatic biosensing method is proposed in [39] that utilizes a tube placed beneath a bed cushion to measure the pressure on the tube. Acquired biosignal is used for pneumonia detection using pressure sensors based on thermal flow principle. However, issues of signal-to-noise ratio and high background noise deteriorate classification results.

2.5.3 Ambulatory Approaches

Apart from sound-based techniques and wearable sensor devices, only a few studies have investigated the prospect of ambulatory cough monitoring.

To circumvent the shortcomings of audio-based techniques, a study employed a plethysmography system that can measure the changes in chest volume caused by coughing. One method is optoelectronic plethysmography, which uses a video recorder to capture the motion of the subject's abdomen. Special reflective markers put at strategic locations on the abdomen enable image processing algorithms to calculate the abdomen's volume. Cough detection can be accomplished through statistical analysis of volume data. However, it is only appropriate for laboratory use because of the video recording requirements of optoelectronic plethysmography [28].

A chest impedance belt is proposed as a viable solution besides general ambulatory applications. The impedance across the chest is proportional to the amount of air contained within—and thus the volume of—the chest. Thus far, published chest impedance solutions have been bulky and obtrusive [36] and are not particularly accurate predictors of cough. However, advancements in electronic textile technology may offer novel answers to these problems [37].

A flow sensor may be used to determine the rate of respiratory airflow. A frequently used flow sensor is secured in place by an ear strap. A thermistor or thermocouple is integrated into the cannula, and it detects the intranasal airflow rate by measuring the temperature variations generated by inhalation and expiration. However, this gadget is incapable of capturing oral airflow. Since the majority of air expelled during a cough is through the mouth, it has a relatively limited capacity for detecting cough occurrences [38]. A comparison of cough detection approaches is presented in Table 5.

In early 2020, roughly 45% of the world's population owned a smartphone, rising to more than 90% in some parts of the world. Sensors, software, and processors of sufficient specification are commonly used in such devices to support accurate cough recognition systems. Therefore, the adaptation of mobile devices as cough monitors is very attractive [29]. Three categories of cough detection approaches are mentioned in Table 5. Type of sensor, placement and biomarker detection are mentioned for each approach along with some limitations.

2.6 Machine Learning Algorithms

Researchers use numerous algorithms to detect coughs in cough-related diseases and even to detect COVID-19 via cough [42]. We can divide machine learning approaches comprised of various algorithms into conventional and unconventional approaches. Statistical methods and machine learning models are conventional approaches, while deep learning methods that use neural networks are counted as unconventional approaches. Categories of machine learning algorithms are presented in Fig. 3.

Table 5 Categories of cough detection approaches

Approaches	Sensor/device	Placement	Biomarker	Conformity level	Limitations
Sound based approaches	Non-contact microphone [39]	Nearby subject	Sound signal	High	Require proximity to the sensor, background noise
	Contact microphone [40]	On body	Sound signal	Normal	Constrained environment, noise
	AI4COVID—mobile microphone [34]	Carry mobile phone	Sound	High	Short-term monitoring, privacy concerns, background noise
Wearable devices and other systems	Flusense (thermal camera) [35]	Deployed in room	Thermographic images	High	Obstruction in field of view of camera, constrained environment
	cECG [32]	Beneath pillowcase	Heart rate variability	High	Low accuracy, constrained environment, no portability
	cEMG [32]	Beneath pillowcase	Skin conductance	High	Constrained environment, noise, no portability
	Leicester cough monitor [41]	Necklace with mic and sound recorder on waistband	Sound signals	Low	Semi-automated, low accuracy, noise

(continued)

Table 5 (continued)

Approaches	Sensor/device	Placement	Biomarker	Conformity level	Limitations
	VitalojAKTM [33]	Chest	Sound	Low	Semi-automated, bulky device, noise
Ambulatory approaches	Plethysmography system (PPG) [28]	Chest	Changes in chest volume	Low	Constrained environment
	Optoelectric plathesmography [28]	In room	Motion of abdomen	High	Low accuracy, obstruction in camera FOV
	Chest impedance belt [37]	Chest	Chest volume	Low	Bulky equipment, low practical application
	Flow sensor [38]	Ear strap	Airflow rate	Low	Only nasal oral airflow rate, low accuracy

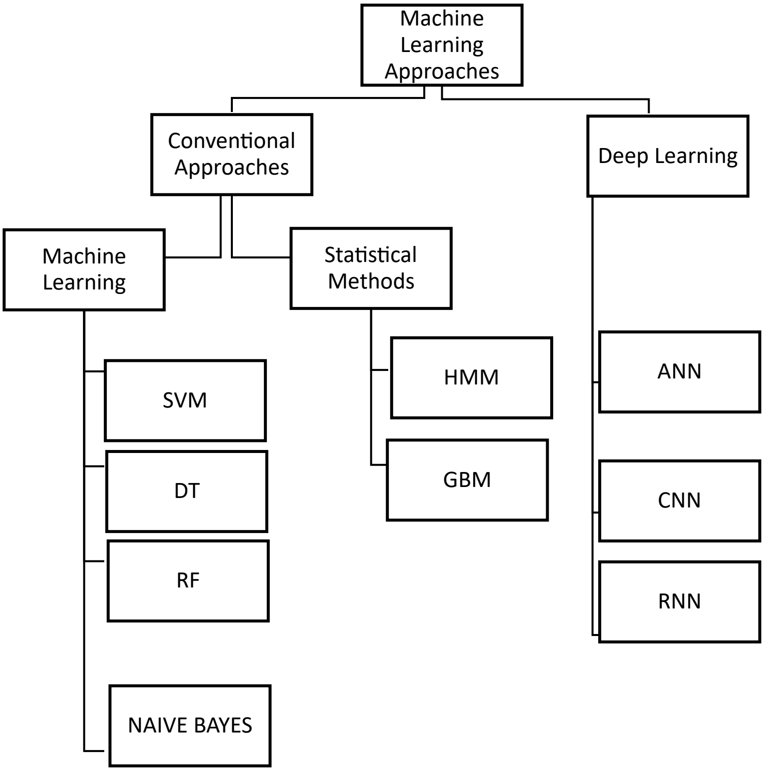

Fig. 3 Machine learning approaches for classification

2.6.1 Statistical Methods and Machine Learning Models

A study proposed Hidden Markov Models (HMMs) to detect cough sounds from continuous ambulatory recordings [43]. The recording equipment comprises a digital sound recorder and a chest-worn microphone. Study of [44] developed a monitoring system capable of differentiating between voluntary coughing and speaking in healthy individuals. A Decision Tree (DT) based discriminator was used to perform classification between various cough events.

The purpose of study [41] is to validate the Leicester Cough Monitor (LCM), an ambulatory cough monitor that is automated and based on sound. The validation method was built using HMM. An Artificial Neural Network (ANN) and a Support Vector Machine (SVM) classifier are combined to monitor cough detection in tuberculosis patients using frequency feature extraction such as Mel-Frequency Cepstral Coefficients (MFCC) features of cough signal [45]. Cough segments in audio recordings are identified using a Random Forest (RF) classifier [31], which can reconstruct the cough signals. The study was done using a low-cost microphone for cost-effective application. Mobi Cough [46] is a forecasting tool that combines the Gaussian Mixture Model with the Universal Background Model (GMM-UBM) to predict cough patterns. System was developed using a low-cost mobile device for data collection. To detect coughing or sneezing episodes, a smartwatch [47] records sound and runs parametric prediction analysis on data. Using univariate and multivariate time series cough data HMM was trained to perform the cough revealing and classification [48].

The power spectral density of cough sounds is determined under various air quality circumstances using a recognition system based on principal component analysis (PCA) and SVM [49]. GMM-UBM classification model was trained using MFCC features to perform the classification [50].

2.6.2 Deep Learning Approaches

A simple threshold method was used to distinguish between several phases of dry and wet coughs, and it was discovered that dry coughs represented a low energy impact [51]. The collected data was used to train an ANN, which provided accurate cough duration and cough recognition using information from several sensors [52].

For cough identification, a convolutional neural network (CNN) is used [53], in conjunction with a mathematical model for sound-based cough analysis. This study constructs a machine-learning-based classifier for asthma cough sounds. In [54], the authors constructed a model by the name of WheezD for the detection of wheeze. An algorithm was developed to extract the respiration sample from the sound recording. Sound was converted to a two-dimensional spectro-temporal picture and created a wheeze detection model using a CNN.

AI4COVID-19 [34], an artificial intelligence-based screening tool for COVID-19 was developed to differentiate between COVID-19 coughs and various other forms of coughs. The cough detection engine determines whether the input sound is a cough and then forwards it to the AI engine to differentiate between COVID-19 and non-COVID-19 coughs using a CNN model. Flu Sense [35] utilizes a novel edge-computing sensor technology, models, and data processing pipelines to monitor crowd behavior and influenza-related signs such as coughing. It employs a microphone array, a thermal camera, and a neural computation engine to passively and continuously evaluate speech and cough sounds, as well as changes in crowd density in real-time.

Studies related to implementation of ML algorithms for detection of cough using accelerometry data are very few. So, this aspect of automated cough detection system is open for experimentation and implementation. However, conventional and unconventional approaches can provide significant results depending upon the application. Table 6 states machine learning algorithms their general applications along with some pros and cons.

Table 6 Summary of several machine learning approaches

Study	Algorithms	Computation cost	Most applied for	Pros	Cons
[31, 43]	HMM	Low	Auditory signals	Fast	Manual feature extraction
[46, 50]	GMM-UBM	Low	Auditory	Fast	Manual feature extraction
[44]	DT	Low	Ambulatory data	Easy scaling, automatic feature extraction, high accuracy	Prone to overfitting
[31]	RF	Low	Ambulatory	Little outlier impact, fast, less overfitting	Sensitive to dataset features
[45, 49]	SVM	Low	Ambulatory	Better for classification, handle high dimensional data, handle outliers	Slow for larger datasets, sensitive to hyperparameters
[33]	NB	Low	Auditory	Real-time predictions, scalable	Require efficient training data, low estimation
[52]	ANN	Normal	Both	Automatic feature extraction	Require larger dataset
[54]	CNN	High	Image processing	Better feature extraction, adaptable architecture	Complex implementation, require large dataset
[22]	RNN	High	Speech recognition	Memory, better predictions	Require large dataset

3 Research Methodology

Essential research stages such as data collection, preparation and training machine learning models are stated in upcoming sections.

Several studies have used a variety of methods for cough monitoring, most of which are based on sound-based systems or wearable sensors. These techniques also highlighted questions about the user's privacy and suitability for long-term monitoring. Mobile phones are extensively used and are equipped with a variety of sensors; they are considered most efficient for long-term monitoring and compliance without invading privacy or raising cost of detection systems. The proposed system categorizes activities of coughing and breathing into three classes, based on 3D

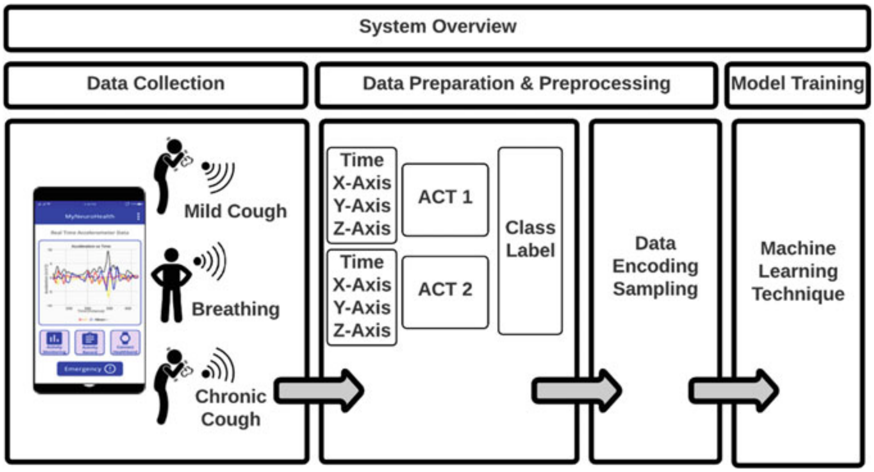

Fig. 4 System overview of research methodology

accelerometer data collected from the user's smartphone. The proposed framework and its various stages are illustrated in Fig. 4.

3.1 Data Collection of Cough

The system collects data from the user via MyNeuroHealth application. The application's architecture and working is described in [55]. Application collects data from the patient's body using the accelerometer embedded in the mobile phone. As operating systems tend to limit the sampling rate of embedded accelerometers, this results in non-uniformly sampled data. We observed that during data collection, the operating system increased the sampling rate from 8 to 20 samples/s in response to previously recorded acceleration values and battery power levels. Thus, real-time pre-processing of the data is used to ensure a uniform sampling rate of 15 samples/s using linear interpolation. The generated data is synced with the user's mobile device and kept in a distant database.

Cough and breathing activities were captured and recorded in an unconstrained environment. As the user carried mobile device throughout the day, we were able to segregate the cough and breathing events in accelerometer data. Additionally, the user was documenting and manually identifying coughing episodes at various points in time. Manual and automated labeling were used in conjunction to accurately identify the occurrence of a specific event at a certain time.

The data collection period was one month. Throughout that period, numerous coughing and breathing incidents were recorded. Coughs were classified as light or persistent. Mild coughing was defined as a shift in the user's pectoral muscles' action, whereas chronic coughing was defined as a cough of high intensity with a

Table 7 Information regarding volunteers and data collection

Volunteers information				No of instances			
No	Gender	Age	Status	Mild cough	chronic cough	Breathing	Total
1	Female	60	Healthy	4000		1000	5000
2	Male	35	Covid patient		3000	2000	5000
3	Male	30	Healthy	2500		1500	4000
4	Female	40	Covid patient		3500	1500	5000

longer duration and more severe muscular reflex. Breathing was recorded while the user was at rest, lying down, sitting, or performing other tasks. Normal breathing was captured using a mobile phone placed on the user's chest. Diaphragmatic muscle action presented a distinct pattern of breathing for each subject.

Table 7 provides detailed information of volunteers; identities of volunteers were kept anonymous for privacy. Data was collected from equal number of healthy and COVID patients of both sexes and having ages between 30 and 60 years under the guidance of medical doctors. A subset of collected data points is presented in Table 7 for reference.

3.2 Sensor Placement

The data is obtained using a mobile phone placed in the individual's upper-left pocket, as illustrated in Fig. 5. The device is worn on the upper left chest side to record the movement and rhythm of the pectoral muscles during coughing and breathing events. Figure 5 also visualizes the x, y, and z acceleration data associated with a given action.

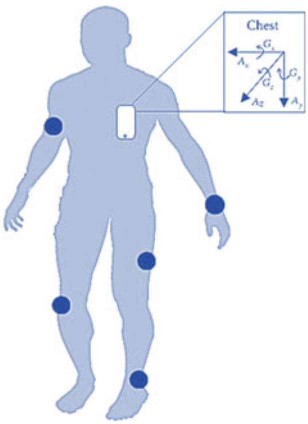

Fig. 5 Sensor placement on chest

3.3 Data Processing

Every dataset has some noise as a result of the data gathering procedure for a variety of reasons. It could be sensitivity of the sensor, external noise, or undesired artifacts. Missing samples, duplicate values and corrupted instances also contribute to noisy data. Hence, Data require some pre-processing before it can be given as an input to the training algorithm.

As stated earlier, varying sampling rates of accelerometer sensors may result in non-uniformly sampled data. Thus, using linear interpolation, real-time pre-processing of the data is employed to ensure a uniform sampling rate of 15 samples/s. The data was examined manually for duplicate and missing values. The missing values were averaged and filled using a technique called statistical imputation. The data samples were standardized using a customized function that employs a Min–Max technique; during standardization, all values in the dataset are defined within a specified range to simplify data processing for the algorithm, hence reducing computing time and increasing efficiency. Output or labels of our dataset were in generic form or of nominal category. Labels were assigned to cough activities and breathing. These categorical labels required encoding so they can be given as input to model. OneHotEncoding function was used in python to automatically encode all the instances without giving priority to any class. For data set 3 columns were obtained against three categories represented as dummy variables, fourth column was removed to avoid dummy variable problem. To diversify the learning process, the training model dataset is randomly picked, allowing it to quickly connect correlated values and find underlying patterns. This is also done in customized simulator before loading dataset values into the training model.

3.4 Model Training

For model training, dataset gathered using MyNeuroHealth application is used [56], and further instances collected using MyNeuroHealth for generating test set and are used in real-time testing. Each recorded activity contains 500 data samples of x, y, and z acceleration, according to the sampling rate. Several models use data after pre-processing to determine the best possible detection accuracy. The training models are then validated by employing tenfold cross-validation.

We evaluated dataset over both supervised and neural networks techniques to acquire results and to see the differences in the results computed by these algorithms. WEKA and MATLAB are utilized for implementing various algorithms.

4 Results and Discussion

This section presents data findings in the form of results and interpretation of results.

There was total of 19,000 instances gathered in a dataset. This dataset was deemed sufficient for testing the system, as adding more instances did not result in further improvement of the machine learning model. A mild cough and chronic cough samples contributed 6,500 instances, and breathing samples contributed 6000 instances. The mobile phone was collecting data periodically with 30 s window. Each monitoring period lasts 30 s resulted in the collection of 500 samples. Collected cough data is 13 min long, whereas breathing data is 6 min long.

A performance comparison is drawn between several machine learning algorithms in terms of accuracy, RF and SVM are implemented using WEKA while MATLAB is utilized for implementation of ANN. Understanding important parameters is essential to evaluate the performance of a training model. Some of the most important performance parameters are Confusion Matrix, Error Histogram and Kappa statistic. Confusion matrix provides information about classified and misclassified instances while kappa determines how well the model learned on provided data.

First, we train our model with J48 DT and evaluate its performance, J48 is a statistical classifier that generates a decision tree using the C4.5 algorithm. Our data set contains 19,000 instances of coughing and breathing. We use tenfold cross-validation to test the model's performance. Model obtains accuracy of 86.6% which means 16,470 instances are correctly classified and 2530 are misclassified. Kappa value of 0.8 is also considered to be a sign of efficient learning. Summary of J48 performance is presented in Fig. 6.

RF performance is evaluated after DT. RF is the combination of multiple individual DTs which also makes it an ensemble model. RF performed 3% better than DT on same dataset. Accuracy of 89.12% is achieved. In terms of computation, RF is slightly slower than a DT. Kappa and mean error values stated in Fig. 7 depicts efficient learning of model.

SVM is implemented using SVM library available in WEKA, again for comparative analysis we utilized similar data set as in previous models. SVM correctly classified 79.9% of instances and misclassified remaining samples. However, the mean error is low but kappa value is also lower as in comparison to previous models. It is visible from confusion matrix in Fig. 8 that SVM is trained less efficiently for mild and chronic cough classes.

ANN was also trained on provided dataset. Accuracy of 80.3% is obtained which is the average of training, validation and testing accuracies. Dataset is divided into 75% training instances, 15% reserved for testing and 15% for validation. Classes 1, 2 and 3 are presenting classes of mild, chronic cough and breathing. 19.7% of instances are misclassified as depicted in 'All Confusion Matrix' block in Fig. 9.

```
Time taken to build model: 0.28 seconds

=== cross-validation ===
=== Summary ===

Correctly Classified Instances      16470       86.6842 %
Incorrectly Classified Instances     2530       13.3158 %
Kappa statistic                     0.8002
Mean absolute error                 0.1239
Root mean squared error             0.2639
Relative absolute error             27.9048 %
Root relative squared error         56.0043 %
Total Number of Instances           19000

=== Detailed Accuracy By Class ===

 TP Rate  FP Rate  Precision  Recall  F-Measure  MCC    ROC Area  PRC Area  Class
 0.811    0.102    0.806      0.811   0.808      0.708  0.908     0.826     Mild
 0.840    0.064    0.872      0.840   0.856      0.783  0.953     0.887     Chronic
 0.957    0.035    0.926      0.957   0.941      0.913  0.982     0.944     Breathing
 0.867    0.068    0.866      0.867   0.866      0.799  0.947     0.884     Weighted Avg.

=== Confusion Matrix ===

    a    b    c   <-- classified as
 5271  799  430 |   a = Mild
 1012 5460   28 |   b = Chronic
  257    4 5739 |   c = Breathing
```

Fig. 6 Evaluation summary of J48 training model

Table 8 compares and contrasts the accuracy of the aforementioned machine learning models. Along with the cross-validation results, the training accuracies are discussed. RF achieved a training accuracy of 100% and a validation accuracy of 89.1%. The ANN obtained the lowest accuracy for the training set, whereas the SVM obtained the lowest accuracy for the validation set. The results from this study were validated by physicians from partner hospitals.

```
Time taken to build model: 8.15 seconds

=== cross-validation ===
=== Summary ===

Correctly Classified Instances      16933          89.1211 %
Incorrectly Classified Instances     2067          10.8789 %
Kappa statistic                     0.8367
Mean absolute error                 0.1074
Root mean squared error             0.233
Relative absolute error             24.1919 %
Root relative squared error          49.4492 %
Total Number of Instances            19000

=== Detailed Accuracy By Class ===

TP Rate  FP Rate  Precision  Recall  F-Measure  MCC    ROC Area  PRC Area  Class
 0.856   0.088    0.835      0.856   0.845      0.764  0.948     0.912     Mild
 0.864   0.053    0.895      0.864   0.879      0.818  0.973     0.944     Chronic
 0.960   0.024    0.948      0.960   0.954      0.933  0.993     0.978     Breathing
 0.891   0.056    0.891      0.891   0.891      0.836  0.971     0.944     Weighted Avg.

=== Confusion Matrix ===

   a    b    c   <-- classified as
 5561  649  290 |   a = Mild
  862 5613   25 |   b = Chronic
  233    8 5759 |   c = Breathing
```

Fig. 7 Evaluation summary of RF training model

5 Conclusion and Future Work

The accelerometer on a smartphone can detect and classify coughs to avoid the spread of COVID-19 and monitoring symptom severity in patients who may require hospitalization due to infection. We conclude that data gathered from a mobile phone-based sensor in an unrestricted setting can accurately classify cough anomalies associated with COVID-19. Developed system pre-processes and classifies data from the MyNeuroHealth application based on the user's movement patterns. The findings of classification of various activities using DT, RF, SVM, and ANN classifiers show that RF performed approximately 10% better for cough and breathing pattern recognition than other classifiers. There is some overlap between the data points for mild and

```
Time taken to build model: 8.07 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances      15161          79.7947 %
Incorrectly Classified Instances     3839          20.2053 %
Kappa statistic                     0.698
Mean absolute error                 0.1347
Root mean squared error             0.367
Relative absolute error            30.3289 %
Root relative squared error        77.8831 %
Total Number of Instances           19000

=== Detailed Accuracy By Class ===

TP Rate  FP Rate  Precision  Recall  F-Measure  MCC    ROC Area  PRC Area  Class
 0.570   0.075    0.798      0.570   0.665      0.546  0.747     0.602     Mild
 0.841   0.064    0.872      0.841   0.856      0.784  0.888     0.788     Chronic
 0.998   0.161    0.741      0.998   0.850      0.787  0.918     0.740     Breathing
 0.798   0.099    0.805      0.798   0.789      0.703  0.850     0.709     Weighted Avg.

=== Confusion Matrix ===

    a    b    c   <-- classified as
 3706  799 1995 |   a = Mild
  932 5465  103 |   b = Chronic
    9    1 5990 |   c = Breathing
```

Fig. 8 Evaluation summary of SVM training model

chronic cough cases, and certain algorithms such as SVM and DT have lower detection accuracy for these instances. Future work may include integrating AI Engine into the MyNeuroHealth app, improving detection accuracy by incorporating additional sensors such as heart rate, EEG, and skin conductivity into the decision-making process, and developing a stand-alone application to assist patients with respiratory disorders.

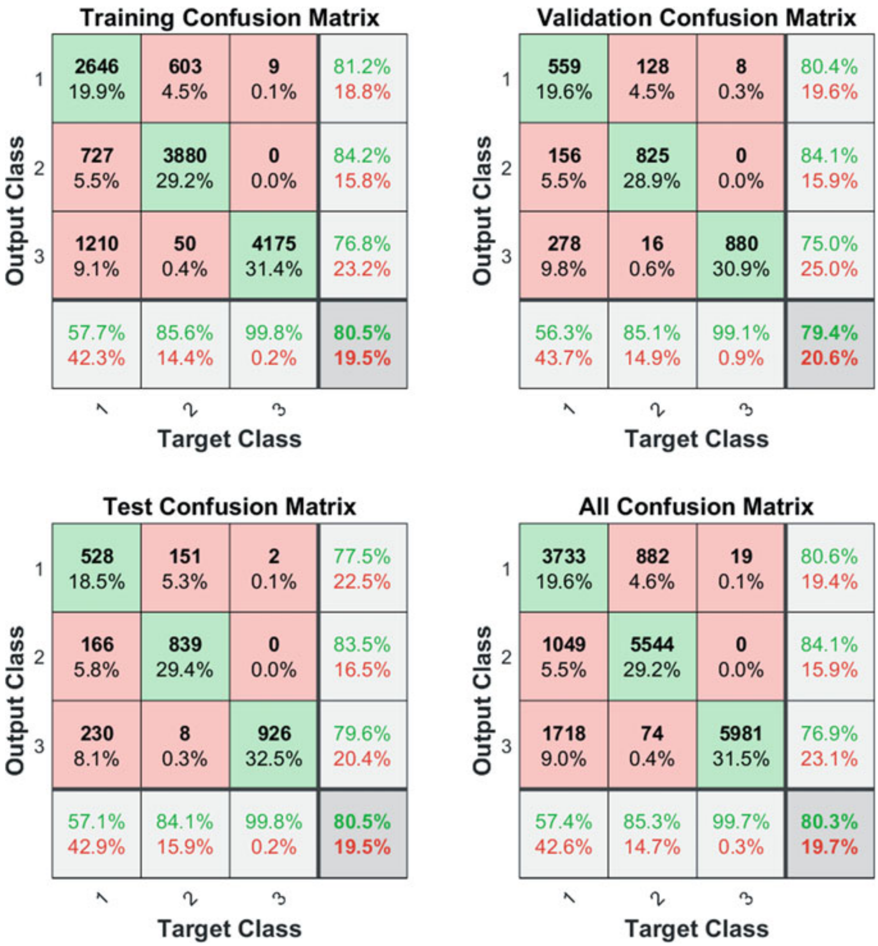

Fig. 9 Confusion matrix of ANN classification model

Table 8 Accuracy comparison of machine learning models

Algorithm	Training accuracy (%)	Cross validation (%)
DT	90.03	86.6
RF	100	89.1
SVM	81.8	79.7
ANN	80.5	80.3

References

1. De Blasio, F., Virchow, J.C., Polverino, M., Zanasi, A., Behrakis, P.K., Kilinç, G., Balsamo, R., De Danieli, G., Lanata, L.: Cough management: a practical approach. Cough **7**, 1–12 (2011)
2. Coronavirus disease (COVID-19). World Health Organization. https://www.who.int/emergencies/diseases/novel-coronavirus-2019. Accessed 6 May 2021
3. Chakaya, J., Khan, M., Ntoumi, F., Aklillu, E., Fatima, R., Mwaba, P., Kapata, N., Mfinanga, S., Hasnain, S.E., Katoto, P.D.M.C., et al.: Global tuberculosis report 2020–reflections on the global TB burden, treatment and prevention efforts. Int. J. Infect. Dis. (2021)
4. Naqvi, S.Z.H., Choudhry, M.A.: An automated system for classification of chronic obstructive pulmonary disease and pneumonia patients using lung sound analysis. Sensors **20**, 6512 (2020)
5. Global alliance against chronic respiratory diseases (GARD). https://www.who.int/gard/publications/en/. Accessed 6 May 2021
6. Thorpe, W., Kurver, M., King, G., Salome, C.: Acoustic analysis of cough. In: The Seventh Australian and New Zealand Intelligent Information Systems Conference, 2001 (2010)
7. Polverino, M., Polverino, F., Fasolino, M., Andò, F., Alfieri, A., De Blasio, F.: Anatomy and neuro-pathophysiology of the cough reflex arc. Multidiscip. Respir. Med. **7**, 1–5 (2012)
8. Mannino, D.M., Ford, E.S., Redd, S.C.: Obstructive and restrictive lung disease and markers of inflammation: data from the Third National Health and Nutrition Examination. Am. J. Med. **114**, 758–762 (2003)
9. Huber, J., Stathopoulos, E.T.: 2 Speech breathing across the life span and in disease. In: The Handbook of Speech Production, p. 13 (2015)
10. Coronavirus (COVID-19) overview. WebMD. https://www.webmd.com/lung/coronavirus. Accessed 6 May 2021
11. Coronavirus disease 2019 (COVID-19) - symptoms and causes. Mayo Clinic. https://www.mayoclinic.org/diseases-conditions/coronavirus/symptoms-causes/syc-20479963. Accessed 6 May 2021
12. Coronavirus disease 2019 (COVID-19) – symptoms. Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/symptoms.html. Accessed 6 May 2021
13. Vahey, G.M., Marshall, K.E., McDonald, E., Martin, S.W., Tate, J.E., Midgley, C.M., Killerby, M.E., Kawasaki, B., Herlihy, R.K., Alden, N.B., et al.: Symptom profiles and progression in hospitalized and nonhospitalized patients with coronavirus disease, Colorado, USA, 2020. Emerg. Infect. Dis. **27**, 385 (2021)
14. Guan, W.-J., Ni, Z.-Y., Hu, Y., Liang, W.-H., Ou, C.-Q., He, J.-X., Liu, L., Shan, H., Lei, C.-L., Hui, D.S.C., et al.: Clinical characteristics of coronavirus disease 2019 in China. N. Engl. J. Med. **382**, 1708–1720 (2020)
15. Chow, E.J., Schwartz, N.G., Tobolowsky, F.A., Zacks, R.L.T., Huntington-Frazier, M., Reddy, S.C., Rao, A.K.: Symptom screening at illness onset of healthcare personnel with SARS-CoV-2 infection in King County, Washington. JAMA **323**, 2087–2089 (2020)
16. Larsen, J.R., Martin, M.R., Martin, J.D., Kuhn, P., Hicks, J.B.: Modeling the onset of symptoms of COVID-19. Front. Public Health **8**, 473 (2020)
17. Hitchcock, P., Chamberlain, A., Van Wagoner, M., Inglesby, T.V., O'Toole, T.: Challenges to global surveillance and response to infectious disease outbreaks of international importance. Biosecur. Bioterror. **5**, 206–227 (2007)
18. Carvalho-Schneider, C., Laurent, E., Lemaignen, A., Beaufils, E., Bourbao-Tournois, C., Laribi, S., Flament, T., Ferreira-Maldent, N., Bruyère, F., Stefic, K., et al.: Follow-up of adults with noncritical COVID-19 two months after symptom onset. Clin. Microbiol. Infect. **27**, 258–263 (2021)
19. Drugman, T., Urbain, J., Bauwens, N., Chessini, R., Valderrama, C., Lebecque, P., Dutoit, T.: Objective study of sensor relevance for automatic cough detection. IEEE J. Biomed. Health Inform. **17**, 699–707 (2013)

20. Cohen-McFarlane, M., Goubran, R., Knoefel, F.: Comparison of silence removal methods for the identification of audio cough events. In: 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2019)
21. Miranda, I.D.S., Diacon, A.H., Niesler, T.R.: A comparative study of features for acoustic cough detection using deep architectures. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2019)
22. Monge-Álvarez, J., Hoyos-Barceló, C., Lesso, P., Casaseca-de-la-Higuera, P.: Robust detection of audio-cough events using local Hu moments. IEEE J. Biomed. Health Inform. **23**, 184–196 (2018)
23. Drugman, T., Urbain, J., Dutoit, T.: Assessment of audio features for automatic cough detection. In: 2011 19th European Signal Processing Conference (2011)
24. Martinek, J., Zatko, T., Tatar, M., Javorka, M.: Distinction of cough from other sounds produced by daily activities in the upper airways. Bratisl. Lek. Listy **112**, 120–124 (2011)
25. Kosasih, K., Abeyratne, U.R., Swarnkar, V., Triasih, R.: Wavelet augmented cough analysis for rapid childhood pneumonia diagnosis. IEEE Trans. Biomed. Eng. **62**, 1185–1194 (2014)
26. Hoyos-Barceló, C., Monge-Álvarez, J., Shakir, M.Z., Alcaraz-Calero, J.-M., Casaseca-de-La-Higuera, P.: Efficient k-NN implementation for real-time detection of cough events in smartphones. IEEE J. Biomed. Health Inform. **22**, 1662–1671 (2017)
27. Monge-Alvarez, J., Hoyos-Barceló, C., Dahal, K., Casaseca-de-la-Higuera, P.: Audio-cough event detection based on moment theory. Appl. Acoust. **135**, 124–135 (2018)
28. Amoh, J., Odame, K.: Technologies for developing ambulatory cough monitoring devices. Crit. Rev. Biomed. Eng. **41**, (2013)
29. Hall, J.I., Lozano, M., Estrada-Petrocelli, L., Birring, S., Turner, R.: The present and future of cough counting tools. J. Thorac. Dis. **12**, 5207 (2020)
30. Proaño, A., Bravard, M.A., Tracey, B.H., López, J.W., Comina, G., Zimic, M., Coronel, J., Lee, G.O., Caviedes, L., Cabrera, J.L., et al.: Protocol for studying cough frequency in people with pulmonary tuberculosis. BMJ Open **6**, (2016)
31. Larson, E.C., Lee, T., Liu, S., Rosenfeld, M., Patel, S.N.: Accurate and privacy preserving cough sensing using a low-cost microphone. In: Proceedings of the 13th International Conference on Ubiquitous Computing (2011)
32. Takano, A., Ishigami, H., Ueno, A.: Non-contact measurements of electrocardiogram and cough-associated electromyogram from the neck using in-pillow common cloth electrodes: a proof-of-concept study. Sensors **21**, 812 (2021)
33. Shi, Y., Liu, H., Wang, Y., Cai, M., Xu, W.: Theory and application of audio-based assessment of cough. J. Sens. **2018**, (2018)
34. Imran, A., Posokhova, I., Qureshi, H.N., Masood, U., Riaz, M.S., Ali, K., John, C.N., Hussain, M.I., Nabeel, M.: AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app. Inform. Med. Unlocked **20**, 100378 (2020)
35. Al Hossain, F., Lover, A.A., Corey, G.A., Reich, N.G., Rahman, T.: FluSense: a contactless syndromic surveillance platform for influenza-like illness in hospital waiting areas. In: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 4, pp. 1–28 (2020)
36. Clarenbach, C.F., Senn, O., Brack, T., Kohler, M., Bloch, K.E.: Monitoring of ventilation during exercise by a portable respiratory inductive plethysmograph. Chest **128**, 1282–1290 (2005)
37. Coyle, M.A., Keenan, D.B., Henderson, L.S., Watkins, M.L., Haumann, B.K., Mayleben, D.W., Wilson, M.G.: Evaluation of an ambulatory system for the quantification of cough frequency in patients with chronic obstructive pulmonary disease. Respir. Med.: COPD Updat. **4**, 137–138 (2006)
38. Drugman, T., Urbain, J., Bauwens, N., Chessini, R., Aubriot, A.-S., Lebecque, P., Dutoit, T.: Audio and contact microphones for cough detection (2020). arXiv preprint arXiv:2005.05313
39. Hadjileontiadis, L.J.: Lung sounds: an advanced signal processing perspective. Synth. Lect. Biomed. Eng. **3**, 1–100 (2008)
40. Rao, A., Huynh, E., Royston, T.J., Kornblith, A., Roy, S.: Acoustic methods for pulmonary diagnosis. IEEE Rev. Biomed. Eng. **12**, 221–239 (2018)

41. Birring, S.S., Fleming, T., Matos, S., Raj, A.A., Evans, D.H., Pavord, I.D.: The Leicester Cough Monitor: preliminary validation of an automated cough detection system in chronic cough. Eur. Respir. J. **31**, 1013–1018 (2008)
42. Preethi, S.R., Revathi, A.R., Murugan, M.: Exploration of cough recognition technologies grounded on sensors and artificial intelligence. In: Internet of Medical Things for Smart Healthcare, pp. 193–214. Springer (2020)
43. Smith, J., Owen, E., Earis, J., Woodcock, A.: Effect of codeine on objective measurement of cough in chronic obstructive pulmonary disease. J. Allergy Clin. Immunol. **117**, 831–835 (2006)
44. Martinek, J., Tatar, M., Javorka, M.: Distinction between voluntary cough sound and speech in volunteers by spectral and complexity analysis. J. Physiol. Pharmacol. **59**, 433–440 (2008)
45. Tracey, B.H., Comina, G., Larson, S., Bravard, M., López, J.W., Gilman, R.H.: Cough detection algorithm for monitoring patient recovery from pulmonary tuberculosis. In: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2011)
46. Pham, C.: MobiCough: real-time cough detection and monitoring using low-cost mobile devices. In: Asian Conference on Intelligent Information and Database Systems (2016)
47. Nguyen, K.A., Luo, Z.: Cover your cough: detection of respiratory events with confidence using a smartwatch. In: Conformal and Probabilistic Prediction and Applications (2018)
48. Teyhouee, A., Osgood, N.D.: Cough detection using hidden markov models. In: International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation (2019)
49. Wang, X., Zhao, X., He, Y., Wang, K.: Cough sound analysis to assess air quality in commercial weaner barns. Comput. Electron. Agric. **160**, 8–13 (2019)
50. Hee, H.I., Balamurali, B.T., Karunakaran, A., Herremans, D., Teoh, O.H., Lee, K.P., Teng, S.S., Lui, S., Chen, J.M.: Development of machine learning for asthmatic and healthy voluntary cough sounds: a proof of concept study. Appl. Sci. **9**, 2833 (2019)
51. Chatrzarrin, H., Arcelus, A., Goubran, R., Knoefel, F.: Feature extraction for the differentiation of dry and wet cough sounds. In: 2011 IEEE International Symposium on Medical Measurements and Applications (2011)
52. Mahmoudi, S.A., Possa, P.D.C., Ravet, T., Drugman, T., Chessini, R., Dutoit, T., Valderrama, C.: Sensor-based system for automatic cough detection and classification. In: ICT Innovations Conference (2016)
53. Kvapilova, L., Boza, V., Dubec, P., Majernik, M., Bogar, J., Jamison, J., Goldsack, J.C., Kimmel, D.J., Karlin, D.R.: Continuous sound collection using smartphones and machine learning to measure cough. Digit. Biomark. **3**, 166–175 (2019)
54. Chatterjee, S., Rahman, M.M., Nemanti, E., Kuang, J.: WheezeD: respiration phase based wheeze detection using acoustic data from pulmonary patients under attack. In: 13th EAI International Conference on Pervasive Computing Technologies for Healthcare-Demos and Posters (2019)
55. Zia, S., Khan, A.N., Mukhtar, M., Ahmad, M., Shahid, J., Sohail, M.: MyNeuroHealth: a healthcare application for the detection of motor seizures. In: IEEE Consumer Communications & Networking Conference (2020)
56. Zia, S., Nawaz Khan, A., Ali, S. E., Mukhtar, M., Shahid, J., Sohail, M.: MyNeuroHealth dataset: activities of daily living, simulated falls and seizure attacks. In: IEEE Dataport (2020)

Psychological and Educational Interventions in COVID-19 Pandemic

Mental Healthcare in the ‘New Normal’: Digital Technologies for Pandemics

Bonnie A. Clough, Mandy Cassimatis, Leila Noorbala, Taraneh Attary, Ali Ghazizadeh, and Kyra Hamilton

Abstract Considerable adverse mental health effects are caused by pandemics, with a global mental health crisis predicated as a result of COVID-19. Existing mental health services already failed to meet population mental health demands prior to 2020, with these rates of unmet need now further exacerbated due to increased prevalence of psychological distress and disrupted service provision. Digital mental health (DMH) services are technologically based tools for mental health assessment and intervention. DMH services will be crucial for meeting the mental health needs of the existing pandemic and will provide a framework to protect against the effects of any future pandemics. These services can be delivered remotely, with efficient use of human and financial resources, and with emerging technologies can be tailored to meet the specific mental health needs of individuals. This chapter provides a discussion on the mental health effects of pandemics and the capacity and efficacy of DMH to reduce unmet need. Whilst the COVID-19 pandemic has resulted in considerable challenges for the provision of mental healthcare, it has also resulted in increased opportunities for innovations in service delivery, which will likely continue well beyond the current pandemic.

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In the context of the COVID-19 pandemic, a global mental health crisis has been predicted [1]. Prior to 2020, mental health coverage failed to exceed 50% in any country, with treatment gaps exceeding 90% even in the well-resourced middle income countries of India and China [2]. That is, more than half of individuals who experienced a mental health concern in any one year failed to obtain treatment. Whilst many countries and individuals have demonstrated exceptional resilience throughout the COVID-19 pandemic, an exponential growth in psychological distress and unmet treatment needs are expected. Indeed, in longitudinal research from the UK, population prevalence of significant mental distress had risen from 18.9 to 27.3% by early April 2020, with women, young people, and those with pre-school aged children most vulnerable [3]. Similar results have been found across studies from China, Spain, Italy, Iraq, the US, Turkey, Nepal, and Denmark, with mitigation of the mental health effects of COVID-19 identified as an international public health priority [4].

There is considerable evidence regarding the acute and long-term effects of pandemics on mental health. In communities affected by outbreaks of the Ebola virus, widespread panic, anxiety, depression, and stigmatisation and social exclusion were reported [5]. Similarly, in outbreaks of previous coronaviruses, including severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS), 33–42% of admitted patients presented with depressed mood, anxiety, insomnia, or impaired memory [6]. In some cases, these difficulties persisted beyond recovery from the physical illness, with 32% of patients meeting criteria for posttraumatic stress disorder (PTSD) post-illness [6]. In India, which has globally reported one of the highest rates of COVID-19 infection, mental health issues including stress, anxiety, depression, insomnia, denial, anger, and fear have been reported being of increased prevalence within the population [7]. Increases in addictive behaviours, such as smoking and alcohol use, have also been observed during the pandemic [8], which have negative effects for both mental and physical health. During the COVID-19 pandemic, increases in population stress and mental ill-health may be related to the direct effects of COVID-19, such as from issues of grief and loss, contagion-related fears and anxiety, or loneliness and low mood related to social isolation [9]. Others may be related to the secondary effects of the pandemic, such as stress, depression, and anxiety due to financial strain, job insecurity or unemployment, and an uncertain future [9]. Indeed, at the time of writing, these stressors remained relevant worldwide with the global pandemic still far from reaching resolution nearly two years after first recognition. In cross-cultural research comparing depression and anxiety in Iran and China, the psychological effects experienced from the pandemic were also found to vary according to factors such government responses, media dissemination of information, and perpections of virus contagion and effects [10]. Globally, the pandemic has and continues to cause significant upheaval and stress for many individuals. These increases in psychological distress have been reported by individuals across the lifespan.

Children and young people have faced unprecedented stressors and challenges during the COVID-19 pandemic. A report from UNESCO [11] identified that over 90% of enrolled school learners were affected by school closures occurring across 188 countries worldwide. For children and adolescents these closures represent a loss of social interaction and support, not only from their peers but from their teachers and other adults. For those experiencing psychological distress, such closures also result in a lack of access to resources and personnel (e.g., guidance or counselling officers) that would usually be available [12]. Furthermore, the increased stress experienced by adults during the pandemic (such as from financial or job insecurity) may be directed from parents to children. Increased rates of child abuse, neglect, and exploitation have been reported during previous public health emergencies, such as the Ebola outbreak in West Africa, with similar trends occurring during the current pandemic [12]. In addition to these stressors, many children are facing issues of bereavement, in some cases multiple bereavements, all of which are being experienced in the context of reduced household incomes and availability of support services.

At the other end of the lifespan, there is increasing evidence to support the vulnerability of older adults to psychological distress during the pandemic. Older adults may have more limited access to technologies or other means of accessing accurate information, they may have difficulties remembering to engage in safety behaviours (such as wearing masks or using hand sanitizer), and may experience significant worry and fear regarding the rapid transmission of the virus and high death rate among older populations [13]. In many countries, older adults have also been subjected to the strictest and longest isolation mandates, increasing their risk of experiencing psychological distress associated with these procedures. Taken together, although the risk factors may vary, the psychological distress associated with the COVID-19 pandemic has affected individuals at all stages of life, and our learning from previous pandemics predicts that these mental health effects will persist for many years to come.

Yet despite these increases in psychological distress, many countries are battling these issues with reduced or disrupted mental health services. A recent WHO survey found that mental health service provision was disrupted in 93% of countries worldwide, with the greatest impact being on community and prevention-based services [14]. Disruption may be due to secondment of healthcare workers to front-line services, requisition of facilities and resources for quarantine or other medical services, and unavailability of appropriate personal protective equipment for mental healthcare staff [14]. Mental health services that were already struggling to meet population needs are now at an even greater disadvantage. Simply put, existing healthcare systems do not have the infrastructure or capacity to meet population mental health needs now and in the coming years. Unfortunately, as healthcare systems struggle to meet demands, it is individuals from disadvantaged, vulnerable, or minority groups that are typically most negatively impacted [15]. Healthcare systems will be required to adopt innovative service delivery models to meet these challenges.

To address the mental health crisis borne from the COVID-19 pandemic and to prepare and safeguard against the effects of future pandemics, governments and healthcare providers will need to strategically invest in technologically-based (i.e., digital) mental health services. These services will need to support the delivery of efficacious mental health treatments and supports that can be delivered remotely and with the efficient use of both human (healthcare professionals) and financial resources. Digital Mental Health services are ideally placed to meet this need and have been argued as critical to effective management of the looming mental health crisis [4, 9]. Digital Mental Health (DMH) refers to information and communication technologies for mental health treatment, such as for assessment, counselling, case management, and monitoring [16, 17]. These tools range from self-help digital tools to those designed to improve the efficacy or shorten the treatment time associated with face-to-face treatments [18]. Such technologies include the use of online programs, mobile applications, and telehealth (phone and videoconferencing).

This chapter aims to provide an overview and roadmap of the use of digital technologies to support mental health during the current and future pandemics. Focus is given to: discussing the mental health effects of the COVID-19 pandemic and social groups that are vulnerable to these effects; the capacity of DMH to overcome barriers to care and increase access to services now and in the future; and the efficacy of these tools for improving mental health. Examples are provided of the integration of DMH into stepped care service delivery. Strategies to protect against the effects of the current and future pandemics, such as through promoting resilient healthcare workforces, are also discussed. This chapter is intended to provide a synthesis of extant research from the DMH and pandemic mental health fields, as well as to draw attention to particular areas requiring attention to improve mental health now and into the future.

1 Mental Health During COVID-19

The COVID-19 pandemic has resulted in increased prevalence of mental health concerns, with predictions that many of these mental health problems will have long-term effects. One of the most commonly reported mental health effects of COVID-19 has been depression, which during the COVID-19 pandemic was reported as seven times higher than the comparable period a few years earlier [19]. Similarly, post-traumatic stress disorder (PTSD) has also become widespread in this period [4, 20–22], to the extent that one in ten people have experienced its symptoms during the COVID-19 pandemic to date [23]. These findings align with previous research showing that mental health issues, PTSD, and depression are associated with trauma caused by deadly pandemics [24–26]. Other pandemic-related mental health problems include anxiety, stress, psychological distress [4], traumatic stress [27], mood disorder symptoms [28], obsessive–compulsive disorder (OCD) [29], acute stress, dementia, insomnia [30], and sleep disorders [31]. With such large and diverse mental health difficulties reported, it is imperative to better understand the patterns and needs of populations now and into the future, in order to coordinate and enact successful and efficient preventive and curative policies. In particular, it will be of importance to identify and support those vulnerable to adverse mental health experiences during pandemics.

1.1 Vulnerability in Individuals with Pre-Existing Mental Disorders

The impact of COVID-19 can be more catastrophic for people with pre-existing physical or mental health disorders [20, 32–34]. Some of the COVID-19 related factors that are thought to contribute to worsening mental health issues among psychiatric patients include "lack of access to primary care or outpatient clinics, increased financial difficulty, the personal concern of contracting COVID-19, long duration of staying at home, and delays in delivery of psychotropic medications" [p. 104, 20], which may increase feelings of hopelessness and even suicidal thoughts. Furthermore, individuals with anxiety and mood-related disorders are more likely to isolate themselves voluntarily and tend to experience more frequent distress compared to those without these conditions [34].

Specific pre-existing mental health disorders have also been associated with increased exacerbation and severity of psychological distress and underlying psychiatric symptoms during the COVID-19 pandemic. For example, pre-existence of autistic-related characteristics directly increased negative emotional response during the pandemic [35]. Pandemics may also intensify the symptoms associated with schizophrenia. Due to pre-existing communication difficulties individuals with schizophrenia have in typical situations [36] and need of social support for recovery [37], social distancing can be particularly harmful for recovery and symptom management in this group [38]. Furthermore, due to factors such as impairments in insight and decision-making capacity, individuals with schizophrenia may have difficulty adapting to new hygiene standards that prevent viral transmission [38, 39]. Conversely, individuals with OCD may experience increased stress due to excessive attention to hygiene, in particular, when exposed to a bombardment of news and information about the pandemic across media platforms [40]. For other conditions, a lack of clarity or even conflicting information has been reported regarding the effects of the COVID-19 pandemic among individuals with pre-existing mental disorders, such as those with attention deficit hyperactivity disorder (ADHD) or bipolar disorder [41, 42].

Children are also a vulnerable group for experiencing increased mental health difficulties during pandemics. Specific to children and adolescents with pre-existing mental health concerns, increases in anxiety-related symptoms, obsessive–compulsive symptoms, autism-related symptoms, self-harm and suicidality, and stress have been observed [12]. In addition, the COVID-19 pandemic has had an adverse effect on the mental health of children who need special education, such as those with autism spectrum disorder [12]. It may also be more difficult for youth to understand and comply with these pandemic-related restrictions and conditions [43, 44].

Indeed, across the lifespan health services face considerable challenges in providing continuous and effective mental health care to those individuals with pre-existing mental disorders. Further, these challenges are compounded by the increased strain placed on services from the mental health difficulties arising among previously 'well' populations.

1.2 Vulnerability in the Healthy Population

Beyond those with pre-existing mental disorders, increased mental distress has also been observed in previously healthy populations when living in pandemics. Within these formerly non-psychopathological populations, vulnerable groups have been identified. These vulnerable people typically belong to groups that endure extra pressure due to being more susceptible or have greater exposure to infection compared to the general public.

One such vulnerable group is frontline medical staff, such as doctors and nurses who are in direct contact with COVID-19 patients [45–48]. In the current pandemic, these individuals have been faced with a significant increase in working hours, high exposure to patients with COVID-19 [31, 45, 49, 50], and the mental health effects of isolation that often occur after disease exposure or transmission [51]. These factors have led to increased levels of psychiatric symptoms including anxiety, depression [22, 52, 53], insomnia, distress, OCD [29], posttraumatic stress [22, 53, 54], acute stress, and sleep disorders [31]. One review identified that nurses might be at even higher risk of mental health difficulties compared to physicians [46]. Such psychological distress is of particular importance within these populations given the associations between poorer mental health and increased risk of treatment errors, staff turnover, and other negative health and organisational outcomes [55].

Also of increased risk among previously well populations are students. From the beginning of COVID-19, most educational institutions continued to function in online format and via virtual classes and meetings. Disruptions to educational routines is shown to lead to mental health problems such as stress, adjustment disorder, and PTSD in some students [12, 56, 57], with a higher incidence of depression and anxiety among children and adolescents [58]. Masters and doctoral students are also at risk of mental health issues arising from COVID-19, with distress arising as a result of disrupted familial support, infection of family members, loss of loved ones, and decreases in family and individual income combined with the challenges of adjusting to online classes (e.g., lack of peer to peer and student to instructor interactions, higher distractibility, and internet connectivity issues) [59]. There may also be issues with privacy, including collection of personal information and harassment on online platforms [59]. PTSD symptoms [59], traumatic stress [27], anxiety [27, 59, 60], depression [27, 60, 61], and mood disorder symptoms [28] are some of the mental health problems that are reported in university and college students during the COVID-19 pandemic.

Pregnant women have also been highlighted as being particularly vulnerable to the development of psychological distress and disorders during pandemics. Due to social distancing during the pandemic and concerns for mother and child health, pregnant women have reported greater depression and anxiety compared to a meta-analysis of mental health of pre-COVID-19 pregnancies [62, 63]. Highest rates have been reported in Europe and North America compared to east and west Asia [63]. Given the long-term effects pre and post-natal mental health concerns can have for both mother and child, such as through development of secure attachment and bonds, particular attention is needed to provide families with support for navigating these challenges during pandemics.

Further, survivors of COVID-19 are another group vulnerable to developing mental health concerns. Both survivors of COVID-19 and current COVID-19 patients admitted to hospital [64–66] are at a higher risk of psychiatric disorders, dementia, and insomnia [30]. Most patients who are recovering or discharged from hospital also have symptoms of depression, PTSD [29, 66–69], anxiety, obsessive–compulsive symptoms, and insomnia [65]. 80% of COVID-19 survivors were estimated to suffer from one or more long-term symptoms with more than half of the symptom being mental-related such as fatigue, attention disorder, anosmia, anxiety, depression, sleep disorder [70].

Although greater understanding is needed of the long-term biological effects of COVID-19, social factors such as increased isolation and health concerns have been associated with these mental health difficulties among survivors. Given the high global rates of infection, considerable stress is likely to be placed on mental health services in order to support this population.

Due to the COVID-19 pandemic, mental health services globally are facing unprecedented challenges. Increased psychological distress among those with existing conditions as well as among previously healthy populations will result in even further increases in demands for services both during the pandemic and into the future. To meet this increased need and the service restrictions faced during periods of restricted movements, services will need to adopt and scale up new models of services delivery that allow for interaction at a distance and efficient use of resources.

2 Digital Approaches for Improving Mental Health in a Pandemic

The COVID-19 pandemic has forced mental health services to consider alternative ways to provide health care. Public health standards, such as "stay-at-home" orders, social distancing, community containment, and quarantine, are new norms that have changed social relationships, including those between doctors and patients. As a result, many clinics were forced to change their routine activities. For example, in many countries mental health day services and outpatient centers were either stopped or converted to facilitate in-home treatment. As a result, remote patient-centered communications, such as using DMH, provided treatment alternatives while expanding treatment reach. Digital mental health (DMH) services are patient-centered solutions that allow for remote patient care through synchronous and asynchronous technologies, and use of these technologies have been rapidly taken up by health services in COVID-19.

2.1 Need for Digital Mental Health Tools

DMH refers to a broad range of categories such as mobile health (mHealth), health information technology, wearable sensors, telehealth and telemedicine, and personalized medicine [71–74]. In addition, it refers to a broad range of electronic telecommunication technology and psychological services performed over the internet including emails, chatbots, web cameras, and virtual reality (VR) technologies [17]. Support ranges from individual, couple, and group psychotherapy, with qualified therapists providing psychological first aid to those in need, regardless of geographical location. DMH frameworks typically focus on increasing the scalability and access of mental health delivery in counselling, monitoring, and treatment. These services will likely be of particular importance for meeting the mental health needs of vulnerable groups during the pandemic and beyond [9].

The COVID-19 pandemic has presented an opportunity to accelerate the digitization of healthcare services [9, 75]. The market of DMH is anticipated to register robust growth with a compound annual growth rate of 24.69% during the forecast period 2021–2030 [76]. Whilst governments were struggling to meet the mental health needs of populations prior to the COVID-19 pandemic, the economic crises, rise in unemployment rates, and increased prevalence of mental health concerns will negatively affect health budgets and the dissemination of services [77]. For instance, the National Health Service of the United Kingdom reported rising rates of mental health issues that would require an average of £1.1–1.4 billion in additional spending each year [78]. Consequently, many health services will be required to adopt DMH strategies to meet population needs within constrained budgets. Although DMH services have not previously been deployed on such a large scale, considerable evidence does support the efficacy of these approaches.

2.2 Efficacy and Use of DMH Technologies

Although DMH technologies are varied both in type and application, typically the most commonly adopted and supported DMH approaches relate to telehealth, online programs, and mobile applications.

2.2.1 Telehealth and Teleconsulting

Telehealth and consulting refers to the provision of care at a distance, via telecommunications technology. Making online appointments, extending access to specialty services, online ordering of prescriptions, and access to test results through a portal are typical telehealth applications. Telehealth consultations may be of particular use for non-emergency routine care, such as substance abuse [79–81], anxiety and depression [82], OCD [83], insomnia [84], eating disorders [85], and other chronic mental health conditions. Recent online surveys and interviews reveal that many patients have a high level of satisfaction with their participation in these services, even when experienced for the first time [86].

Recent systematic reviews and meta-analyses have also supported the efficacy of telehealth approaches as being as effective as face-to-face treatments for many psychological disorders and treatment approaches [87, 88]. They can also give mental health workers access to information they might not otherwise have. For example, the clinician can directly observe the patient's home environment, providing vital clues about their mental health. In fact, it presents extensively more information about a patient's environment, social and functional factors that affect medical care outcomes and can enhance the patient-clinician relationship, challenge assumptions, highlight implicit biases, and allow for more personalized medical care. Indeed, the American Psychiatry Association (APA) updated its policy on telepsychiatry: "Telemedicine in psychiatry, using video conferencing, is a validated and effective practice of medicine that increases access to care" [89]. The APA supports the use of telemedicine as a legitimate component of a mental health delivery system to the extent that its use is for the benefit of the patient, and protects patient autonomy, confidentiality, and privacy [89]. Teleconsulting services therefore have the potential to remain promising methods for treatment delivery post-pandemic [90, 91].

The electronic prescription of medications has been of particular benefit during the COVID-19 pandemic, when having access to psychotropic medicine was challenging because, in some cases, any pause in taking prescribed medication could cause severe health consequences [92]. To address this problem, extending the prescription amount of narcotic drugs, drug delivery platforms [93], removing the requirement for an in-person assessment before prescribing drugs [94], and financial support in covering medication costs have been implemented to improve the flexible delivery of health services during the COVID-19 pandemic.

Telehealth services may also support the delivery of in-home treatment techniques, accessed via portable health devices. Home-based transcranial direct current stimulation (tDCS) devices are an example of these types of devices. tDCS is a non-invasive, painless brain stimulation device that uses direct electrical currents to stimulate specific parts of the brain by a small amount of current via an electrode patch on the scalp [95]. Home-based tDCS can be self-administered by the person and remotely monitored by professionals using the password-protected app connected to a dedicated server that stores the users' health profile data. tDCS modulates neuronal excitability and therefore affects brain functions such as mood regulation, emotion, and information processing. For example, recent studies demonstrate that non-invasive brain stimulation targeting the prefrontal cortex (F3-anode and F8-cathode montage according to 10–20 EEG placement) can regulate mood [96]. It is also a relatively cheap and tolerable stimulating device with no severe side effects encouraging home use [97]. tDCS is one example of the utilisation of telehealth services to promote greater involvement of the patient in treatment delivery as appropriate.

2.2.2 Online Programs and Smartphone-Based Applications

Online programs are possibly the most well-established form of DMH, with decades of research supporting their efficacy [18, 98, 99]. Infrastructures include software architecture that integrates easily with existing technology, a synchronous broadband connection that makes real-time communication possible, and finally, storage that securely maintains patients' data. Online programs are typically accessed through web browsers and consist of modules or 'sessions' focusing on psychoeducation and skills building. Some programs may incorporate minimal contact with a trained health professional and/or promote psychological support via the use of online forums and discussion groups. Programs exist for a range of disorders, populations, and theoretical treatment approaches [18]. In some countries, such as Australia, these programs may be government funded and considered a first part of 'stepped care' treatment approaches for preventative or low severity psychological presentations [100]. These programs hold considerable advantages to treatment delivery, as they typically require no or minimal therapist input and thus allow for wider reach of services and available resources. As a more recent development to this approach, many programs and psychological techniques can now be accessed on mobile devices, by means of smartphone applications or 'apps'. Whilst these apps may simply facilitate an alternate mode of delivery for psychological interventions and content, others make sophisticated use of the additional technologies available through the Smartphone [16].

Smartphones collect a large variety of sensor-based data by GPS, accelerometer, gyroscope, microphone, phone calls, messages, speed of typing, phone notification management (e.g., clicks, decision, and response time), the screen on/off, light sensor, skin temperature, skin conductance, app usage, social information, and phone-based questionnaires [101]. All these streams are objective measures that are sequentially collected in the context of an individual's natural environments. Furthermore, the repeated real-time sampling of behaviors and lived experiences, known as ecological momentary assessment (EMA), allows the study of micro-processes influencing real-world behavior [102]. There is preliminary support for the clinical utility of smartphone sensor data paired with EMA responses in the assessment and promotion of self-management in psychotic disorders [103, 104]. Also, it could engage in reinforcing or extending evidence-based therapies among treatment options by giving pieces of information about how one's symptoms vary over time [105]. For example, EMA analysis has demonstrated how the COVID-19 pandemic has had a widespread mental health impact among college students [106]. Analysis of data from individuals' smartphones can result in the development of unique patterns of algorithms to measure and predict mental health among individuals and groups.

Digital phenotyping is one such analytical approach, which focuses on the development of a 'digital fingerprint' based on analysis of passive measures from smartphone usage [95]. With further evidence, these type of analysis could be a continuous ecological surrogate for laboratory-based neuropsychological assessment of working memory, memory, executive function, language, and intelligence [107]. Analysis of digital sensor big data by artificial intelligence (AI) technology is a data-driven and evidence-based method for diagnosis and symptom monitoring. In some cases, the prognosis of mania or depression could be diagnosed by analyzing data from digital sensors [108]. Digital phenotyping is beginning to provide clear evidence to stratify patients based on precision medicine that seeks to create treatments applicable to groups of individuals who meet specific characteristics. However, disadvantages include the lack of available technological resources in certain parts of the world and the challenges of developing scalable data collection infrastructure while ensuring patients' data security [109]. In the context of the COVID-19 pandemic, preliminary evidence exists for the use of digital phenotyping. Content analysis of text messages of the Talkspace indicates that people seeking treatment for pandemic-related distress experience more severe COVID-19–related anxiety symptoms than before the outbreak [110]. In addition, in a proof of concept study, digital phenotyping was used to identify changes in schizophrenia, major depressive disorder, and bipolar disorder patients' behavior incited by quarantine [111]. Another study demonstrated the potential of anomaly detection with 89% sensitivity and 75% specificity for predicting relapse in schizophrenia [112].

Online programs and apps will likely form an important part of mental health service delivery in coming years. These treatment options allow for efficient and efficacious use of resources. In addition, the still developing areas of sensor-based technologies and digital phenotyping will allow for increased monitoring, early interventions, and tailoring of services to meet individual needs. For example, some technologies provide patients with a device that can make recordings of the heart and lungs, perform imaging of the ear, mouth, and skin, and detect body temperature remotely to overcome inherent lack of physical contact in DMH approaches [113, 114]. Yet, despite this potential, one of the key challenges facing mental health service providers in the future will be the identification of individuals appropriate for DMH interventions, the effective integration and use of DMH with in-person treatment, and the development of appropriate population level models to support this integration.

A consistent limitation of the DMH research field has been the lack of attention given to implementation and policy driven research [114, 115]. In addition, the implementation strategies adopted, including models and technologies, will be highly dependent on each cultural and healthcare context. For example, in low income countries that have greater mobile than fixed line infrastructure, mobile apps may be more easily integrated than online programs. Similarly, the extent to which digital mental health technologies are integrated into standard care or used as standalone treatments may also be dependent on the staffing and resourceing available within each healthcare context. As such, choices regarding the specific technologies used and models adopted should follow careful consideration and discussion with consumers, clinicians, and policy advisors. To assist in this process a guide for implementation strategies within DMH has been proposed, with stakeholders encouraged to consider strategies from proposed implementation (e.g., conducting structured needs assessments), to implementation (e.g., the creation of practice guidelines for DMH, ensuring practitioner competency) and sustainment phases (e.g., assessing changing needs and preferences over time) [115]. Such an approach would ensure that the adoption of DMH is appropriate for each system and sustainable for longterm treatment support and delivery. Below, we provide an illustration of one such model of adoption, the Stepped Care approach currently being implemented within the Australian Healthcare system.

3 'Stepping Up' to the Challenge

The stepped care approach entails providing a person-centred approach to mental health support that offers services to patients which vary along a spectrum in terms of the level of severity of a mental health disorder regarding the impairment caused, its impact on their functioning and the level of distress they experience. The aims of implementing a stepped care approach are to provide the right service at the right time to each patient [116]. This means that treatments are personally tailored to each patient depending on what level of care they require in the present. Patients can therefore receive a level of care that is appropriate to their needs at any given time. This approach is designed to be integrated with health care services that are provided at a broader level rather than being primarily for autonomous use. This approach is useful for individuals who experience temporary episodes of mental health symptoms, as well as for those who have chronic mental health conditions which involve the severity of symptoms fluctuating over time [117].

The benefits of a stepped care approach include providing the specific level of support that is required by the individual rather than over-expending resources. The individual is provided with the opportunity to self-manage their mental health symptoms insofar as this is appropriate, rather than the health care system committing time and resources that are disproportionate to their needs for support at the time. The stepped care approach is also financially viable for the economy by supporting people with mental health symptoms at both the sub-clinical and clinical levels so that not all clients are provided with intensive support and services if they do not require them [116]. Furthermore, this approach ensures that sub-clinical symptoms of mental health disorders are recognised and addressed before they manifest into more severe presentations of mental disorders. Individuals are hence able to maintain a reasonable level of autonomy while going through the treatment process at any stage due to the accessibility of support and independence that is offered by using DMH treatments, and the option of ongoing monitoring by the patient and health care provider that is offered by this treatment modality. In addition, mental health issues can be addressed at every level of intensity, and thus using the stepped care approach within DMH programs is beneficial to society clinically, socially and economically [118–120].

In Australia, for example, the Stepped Care Approach has been effectively incorporated into the DMH space via a number of programs [e.g., 121–123]. Specifically, programs have been designed to range in intensity from a low level, which typically includes offering a range of self-guided online tools such as self-monitoring tools and psychoeducation resources, to moderate level intensity resources, which may include the addition of interactive online tools for users to work through, at times with intermittent guidance from an online therapist or counsellor. Finally, high intensity supports include regular contact with a mental health professional in conjunction with frequent use of a relevant DMH program, which can involve the mental health professional accessing the work that the patient has done within the online program to monitor progress, provide feedback and incorporate it into the patient's treatment plan. The most intensive level of support often includes undertaking regular risk assessments which are overseen by the mental health professional [116]. Eventually, when the patient's symptoms reduce in severity they are able to maintain their treatment progress by continuing to access remotely accessible support tools. This opportunity for remotely accessible ongoing mental health treatment is particularly well suited to Australians who live in rural and regional areas, where access to traditional mental health services is difficult to obtain. Digital mental health programs that utilise a Stepped Care Approach have been designed to address service gaps in priority areas within the Australian mental health care setting. As such, health professionals have been encouraged to promote and endorse DMH platforms to patients who require various levels of mental health support and/or treatment.

Australians now have a variety of programs to choose from in the digital mental health space where they can receive the right intensity of support to meet their needs. The Australian Government has overseen the development and implementation of the Head to Health digital mental health gateway, which offers consumers access to evidence-based information, advice and free or low-cost telephone and online mental health services and treatment options [124]. An additional option for digital health care is WellMob, which is a website that includes a compilation of social, emotional, and cultural wellbeing resources for Aboriginal and Torres Strait Islander people [125]. Therefore, the DMH space and the use of stepped care in this sphere is currently being implemented across all sectors of society, in terms of location, cultural background, and the severity of mental health symptoms, and would be a useful approach for addressing mental health care in other geographically vast countries.

3.1 A Case Example—Digital Mental Health Applied at a National Level

Tawakana was a 45-year-old male of Aboriginal descent who lived in Northern Queensland in Australia. He had presented to the emergency department of the nearest hospital with alcohol intoxication and comorbid depression. He had reportedly been suffering from symptoms of these mental disorders since he was a teenager after leaving home at 13 years of age due to an upbringing that included an extensive history of trauma involving domestic violence and exposure to substance use as a child. Daku had since been engaged with mental health treatment at that location, which was 624 kms away from his home, a few times over the past 10 years. Each time Daku was admitted to the hospital, he was required to stay for the duration of at least 4 weeks until the acute mental health team had stabilised his mood to the point where his risk profile was significantly reduced, and they had provided effective alcohol detoxification treatment. Therefore, the inpatient visits were costly to the Australian public health system. However, there was no other way for Daku to receive the treatment that he needed to ensure his safe return back to the community, in particular given that he resided in a remote area. The 4-week treatments only tended to last for a maximum period of 3 weeks until Daku relapsed in terms of his depressive mood and was again drinking excessive amounts of alcohol. Therefore, it only provided a temporary fix for the situation.

Shortly after Daku's third visit to the hospital's emergency department for the same issues, a DMH team from a University in the nearest town set up a computer kiosk approximately 10 kms from where Daku lived. The team had established that the locals in the area were very low on digital health literacy so they went into the community to get to know the locals, from young people to the elders of the community. Among the team was a member who was of Aboriginal descent who understood the customs and spoke the language of the people in that community. She facilitated the digital literacy training and educated the community about the purpose of the computer kiosk. She informed them that the rationale behind the use of the kiosk was to provide people who were in need of support for not feeling high spirited and/or who were drinking a lot of alcohol to find information and resources to help them, and that they could also connect with her or another aboriginal health professional from the closest township to help them put in place strategies to support them if things were really challenging. She showed them how they could enter self-monitoring data for mood (which was assessed on a culturally appropriate scale), lifestyle factors (physical activity, diet, weight), and alcohol intake to see where they were at and to send this information on to the health professional at the other end. She then demonstrated how the computer program would guide them on healthy lifestyle, including drinking habits, and help them to consider where they were at with their drinking. She showed them how if their mental state or lifestyle behaviours including alcohol intake, were out of range, an alert would be sent to the health professional who would call them to provide support. She informed them that the information would also be sent to the health care providers they saw in the nearby town infrequently so they could be up-to-date with what was happening with their health. The computer program effectively provided a stepped care approach that involved the delivery of psychoeducation, resources and self-monitoring functions at the most basic level, interactive support via personally tailored tools and games at a moderate intensity level, followed by contact with a health professional at the next intensity level, and finally connection with the acute mental health care team at the nearest hospital at the most intense level (at which patients were deemed high risk). Such a program had the potential to provide regular, ongoing treatment to patients with similar presenting issues to Daku within their remote community and to act as a targeted treatment approach that was geared towards the patient's symptom intensity, with the potential for preventive benefits from symptoms emerging into severe ones that would require hospital admission.

A widely renowned and popularly used stepped care approach for the Australian context which provides guidance to clinicians on how they can best utilise resources with clients to produce effective outcomes is the conceptual framework of implementing e-mental health resources (Reynolds et al., 2015). In her model, Reynolds proposes five emerging clinical practice models, which include: (1) promotion; (2) case management; (3) coaching; (4) symptom-focused treatment; and (5) comprehensive therapy. The integration of clinical skills by the variety of health care professionals that are involved in the care of a patient with a mental health disorder and how this is best done is also considered in Reynold's model. This includes the roles of medical practitioners, pharmacists, psychologists, occupational therapists, social workers, nurses and more. Reynold's model thus provides a useful conceptual framework that can serve as a blueprint for the effective integration of e-mental health services into primary care settings. Ideally, in such settings, the aim is for the digital mental health program or service to effectively complement the role of health care providers rather than to replace them. Therefore, within each program, there is typically the option for the health care provider access to at least some portion of the patient's health information that has been entered for self-monitoring and/or screening purposes. This enables the health care provider to track the patient's progress with mental health symptoms in-between visits. The patient also gains substantial insight into their condition and its impacts on their functioning, as well as ways this can be improved by using the suggested strategies within the program. The art of tailoring the DMH program to each patient means this model provides a cost effective solution to providing ongoing treatment to patients with mental health conditions.

3.2 Case Study 2—Individual Level

Tyler was a 32-year-old woman who presented to her General Practitioner (GP) with concerns about low mood following the birth of her baby 6 weeks prior to her visit. Tyler reported concerns about homicidal thoughts about harming her baby as well as herself. She reported experiencing severe social withdrawal, feelings of loneliness, daily crying, extreme fatigue, lack of motivation to the point where her husband had to tend to the baby when he cried as Tyler was unmotivated to do so, lack of pleasure in usual activities such as watching her favourite comedy shows or reading, irritability, and thoughts of suicidal ideation. Tyler was adamant that she should not take anti-depressant medication as she was currently breast-feeding. Her GP referred her to a psychologist who put Tyler in touch with an online postpartum depression support program. The program included psychoeducation about postpartum depression, and when Tyler started it, she had round-the-clock accessible support from trained counsellors via the chat room that was available in the program should she wish to reach out and start a chat about anything that was bothering her, including if she noticed a sudden worsening of her symptoms. There was also a peer support function within the program that Tyler utilised, which helped to normalise her experience of living with postpartum depression, and assisted with removing the feelings of guilt that she had about her relatively low level of functioning and thoughts about harming her child. The program also featured support resources that her partner could use to better understand what was going on for Tyler. Tyler had online video conference sessions with a psychologist within the program every 2 days initially until there was a marked reduction in her mood symptoms and her homicidal and suicidal ideation. She continued the peer support groups weekly for a period of 10 weeks, and noticed that interacting and staying in touch with the other mothers online via the program also helped to create a sense of social support for her without leaving home. Finally, Tyler's GP and psychologist were able to check in on her symptoms via the program and ensure they were not worsening. As Tyler's needs for support reduced over the following 6 months, she stopped taking part in the peer support groups, reduced her online therapy sessions to once each fortnight, and only used the system to self-monitor her symptoms. She reported this provided her with a sense of reassurance that she was keeping her symptoms at bay whilst ensuring the safety of herself and her baby. She was aware that if there were any increase in her symptoms again that she would immediately receive the kind of support that she needed.

4 Getting Vaccinated—Protecting Against the Mental Health Effects of Pandemics

Thus far, this chapter has discussed strategies for identifying and treating psychological distress as it arises. However, there are preventative steps that should be taken at both the individual and service levels to safeguard against further potential negative impacts of the current pandemic and in preparation for future pandemics. These steps include improving the training of mental health professionals in DMH approaches, paying attention to the mental health and wellbeing of these workers, and integrating mental health treatments holistically with physical health treatment.

4.1 Training a DMH Ready Workforce

The COVID-19 global pandemic has widely been recognised as a catalyst and turning point for patient and clinician adoption of DMH [9, 126]. Worldwide, mental health professionals have had to make rapid adjustments to their practice to incorporate DMH technologies for remote delivery of services. Many of these professionals were required to navigate this steep learning curve with limited previous training or supervision in the use of DMH [9, 127]. Indeed, one Paris-based psychiatric unit reported a reluctance of staff to embrace remote delivery of services prior to the pandemic, but required a shift of 90% of outpatient activity to telepsychiatry during the pandemic [128]. Such transitions and challenges have been observed worldwide. A psychiatric department in Italy reported a greater than 90% shift in service to telepsychiatry, despite "little, if any, experience with telemedicine" and a lack of standardised procedures and platforms for conducting such services [129]. Yet even prior to this rapid adoption, mental health professional capability to use DMH in practice was identified as a major determinant of successful uptake and sustained use.

Mental health professionals consistently report low confidence in, and concerns regarding: their skills to use DMH in practice; capacity to identify clients suitable for DMH treatment; lack of training and experience in this area of practice; and translations of therapeutic skills into a digital environment [130–134]. These barriers and concerns can result in poor service quality and implementation difficulties for mental health professionals engaging in DMH.

The call for greater standardisation of training and competencies in this field has been made by numerous professional bodies [e.g., 135] and researchers [e.g., 136]. Various practice guidelines [137] and policy frameworks exist for specific areas within DMH, for example the European Data Protection Directive and the European Directive on Distance Contracting [138]. However, these guidelines and directives fall short of specifying the behavioural actions and competencies needed for effective DMH practice. Despite the identified need for professional competencies within DMH, to date, only one effort has been made to develop standardised, interprofessional competencies for the field.

In 2017 Maheu and colleagues [139] reported on the development of a "telebehavioral health" competency framework for mental health workers in the United States of America. This competency framework represents a considerable step forward in improving quality of DMH services. However, the framework has key limitations, with the authors identifying that it is only a first step toward consistency in the field. In particular, the framework has a heavy focus on the narrower telehealth (phone and videoconference services) field, with no reference to DMH technologies such as online programs, virtual or augmented reality, biosensors, or artificial intelligence tools. The authors also acknowledged that the competencies are bound to the originating culture and healthcare system framework. Nonetheless, this framework is an invaluable resource for mental health professionals and policymakers incorporating telehealth technologies in service delivery during the current pandemic.

The COVID-19 pandemic has highlighted remote delivery of services as a considerable stress point in healthcare delivery. In buffering against the effect of future pandemics, focus needs to be given to training clinicians in the use of digital technologies (beyond purely telehealth approaches) for providing mental health support. However, before this can occur, agreement needs to be reached on the competencies and standards of practice expected in this area. A consensus-based framework of competencies is required, and whilst overlap may occur, it is likely that such a framework would need to be specific to the country and cultures it services. Such frameworks, and training programs to help clinicians meet competency standards, will improve the quality of services in the current pandemic and ensure that the mental health workforce is digitally ready for future pandemics.

4.2 Protecting the Mental Health of Our Healthcare Professionals

Healthcare workers have been exposed to considerable stressors and adverse conditions during the COVID-19 pandemic and have been identified a as group vulnerable to the experience of psychological disorders. Yet beyond these psychological disorders, many healthcare workers have also experienced distress associated with burnout and moral injury.

Burnout is a syndrome resulting from chronic exposure to high levels of occupational stress and is typically conceptualised as having symptoms of emotional exhaustion, depersonalisation, and reduced personal accomplishment [140]. Moral injury refers to the psychological distress that arises when an action or inaction, such as related to a person's working conditions and requirements, violates their personal values and ethics [141]. Whilst neither of these experiences are considered psychological disorders, both have been associated with elevated psychological distress and increased risk of developing psychological disorders in the future, making them areas of particular concern for healthcare workers. Given the high and prolonged pressures placed on healthcare workers during the pandemic, elevations in rates of burnout [142] are unfortunate but not surprising. In addition, the inability to provide gold-standard levels of care to patients, to due over-burden and under-resourcing, has resulted in distress and moral injury for many workers, with pain likely to be felt well beyond resolution of the pandemic [141].

Specific to mental health professionals, organisations and training providers must pay particular attention to issues of burnout, moral injury, and mental distress now and in coming years. In the context of a growing mental health crisis, it is likely that many mental health professionals will face issues of over-burden and chronic occupational stress as they struggle to meet the mental health needs of their communities. In addition, many mental health professionals may already be experiencing moral injury, with restrictions and resourcing limiting their capacity to provide mental health care consistent with their values or personal ethics. The need for routine support processes, ongoing monitoring, and provision of evidence based treatments has been highlighted as critical to support the longevity of healthcare workforces [141]. Yet, despite this identified need, healthcare workers often fail to present for treatment or support when needed.

Many healthcare professionals fail to seek mental health support when needed, including for issues of occupational stress and burnout [143]. Healthcare professionals experience many of the barriers to care that members of the general public experience, as previously discussed in this chapter. However, they may also experience additional barriers including lack of time due to the burden of work responsibilities, lack of access to appropriate services that are confidential and removed from their profession or place of work, services that are available during their time off (including if working shift work), fears of professional consequences of disclosing mental health difficulties (such as restrictions to registration or practice), and stigma [143, 144]. Stigmatising beliefs that prevent healthcare workers, including mental health professionals, from accessing services are: attitudes held by oneself towards a person or population with the condition or experience (e.g., *a healthcare worker experiencing burnout is lesser than one who is not*: personal stigma); the attitudes a person holds about themself during the experience (e.g., *I should be able snap out of this:* self stigma); attitudes regarding how the general population would view a person with the condition or experience (e.g., *my patients would think less of me if they knew:* public stigma); and the perceived or actual limitations that may be placed upon a person with the experience or condition by society, an organisation or institution (e.g., *I would not be supported if my supervisor or superiors found out:* structural stigma) [144, 145]. For these reasons, it has been argued that supports provided to healthcare workers should be able to be accessed anonymously [55, 144].

Taken together, it is clear that there is a need to support healthcare workers during the COVID-19 pandemic and beyond. Whilst workplace support and monitoring will be needed [141], there is also a push for the development and dissemination of self-help approaches to supporting healthcare workers [146]. The utility of DMH has already been argued as ideal for this purpose [55], particularly with reference to the advantages of anonymity, 24/7 access, and self-paced delivery. However, it is imperative that any DMH interventions be tailored to meet the specific needs and experiences of healthcare workers. Furthermore, they should not only treat existing distress but should also train healthcare workers in resilience and emotion regulation techniques to protect against the experience of future stressors, such as in the long-term recovery from the current pandemic and preparation for future pandemics. For successful adoption, such programs will need to be supported by healthcare organisations, governments, and professional bodies. Addressing the mental health needs of this population will be critical in retaining a healthy and resilient healthcare workforce into the future.

4.3 Placing Mental Health in a Holistic Framework

The importance of addressing the mental health needs of target groups during the COVID-19 pandemic and beyond is undeniable. However, much of the literature to date has focused on these concerns with far fewer papers on COVID-related health behaviours and health communications [147]—factors that have been central in limiting SARS CoV-2 contagion, hospitalizations, and deaths [148]. Tackling the mental health issues brought about by COVID-19 should therefore not be looked at in isolation, especially given key physical health behaviours such as social distancing, handwashing, and facemask wearing, if adhered to, can prevent further lockdowns, stay-at-home orders, and self-isolation directives—factors shown to be associated with mental health issues during the pandemic [149–151].

Over the past year, research has emerged identifying the social psychological determinants of COVID-19 preventive behaviours. This research has shown factors such as self-efficacy, moral norms, intentions, and planning to be reliable predictors of behaviours such as social distancing, handwashing, and facemask wearing [152–155]. Previous research for influenza-related preventive behaviours have shown similar findings [156–158]. Identifying the determinants of behaviours of interest is important as they can potentially be modifiable through intervention; that is, can be targeted in messages or campaigns of behavioural interventions. Digital technologies, as has been shown above for mental health, can be used to target change in and maintenance of these physical health behaviours. For example, Smith et al. [159] tested the efficacy of a theory-based intervention delivered online to promote the avoidance of touching one's face with unwashed hands in samples of Australian ($N = 254$; Study 1) and US ($N = 245$; Study 2) residents. The intervention consisted of behaviour change techniques including imagery, persuasive communication, and planning. Although results revealed a significant increase in avoidance of touching the face with unwashed hands from pre-intervention to follow-up irrespective of intervention condition, exploratory analyses revealed significant effects of the theory-based intervention on behaviour at follow-up in individuals with low pre-intervention risk perceptions. More broadly, systematic review and meta-analytic evidence provides modest support for the use of digital health interventions for improving physical health behaviours and health conditions [160–163].

Although the importance of adhering to COVID-19 preventive behaviours is unequivocal and has a potential indirect link to mental health through preventing further lockdowns, stay-at-home orders, and self-isolation directives, other physical health behaviours have shown more direct links with mental health including physical activity, alcohol misuse, and smoking [164, 165]. For example, research has shown alcohol to be a casual factor for depression [164]. There is also extensive evidence indicating strong direct associations between performance of regular physical activity and improved depressive symptoms and stress levels [163]. Interventions that reduce the use of substances and improve engagement in physical activities are therefore likely to reduce the prevalence of mental disorders. Accordingly, the artificial divisions between mental and physical health need to be removed and DMH treatments should be available in an integrated fashion for both mental disorders and physical health behaviours.

5 Conclusions and Future Directions

The COVID-19 pandemic has been a catalyst for change within mental healthcare. The pandemic has resulted in increased psychological distress in many countries, including among those with pre-existing mental health concerns and those who belong to vulnerable groups. Simultaneously, the pandemic has also resulted in significant services disruptions and loss of resources for mental health provision. Healthcare workers and governments made rapid and often effective transitions to digital health provision. Telehealth, online programs, and apps provide alternatives to in person treatment delivery, that reduce barriers to care, increase treatment reach, and reduce treatment costs. Yet challenges remain for the ongoing integration of these services to both target the ongoing effects of the current pandemic and prepare for any future pandemics.

Stepped care approaches may assist governments and policy makers in the development of treatment models to support the ongoing integration of DMH services. These approaches focus on the effective utilisation of digital and in person services to ensure individuals receive appropriate mental health treatment based on symptom severity, risk, and other social and health considerations. It is likely that such models will need to be specific to cultural and healthcare contexts in order to adequately account for these factors. Future research will be needed to develop and test these models, in consultation with patients, healthcare providers, and policymakers. In addition, focus needs to be given to the development of supportive training resources and programs to facilitate effective practice within these DMH treatment frameworks.

Throughout this process of evolving healthcare, attention needs to be given to those providing the care. Healthcare workers are a particularly vulnerable group to the experience of mental distress, stress, and burnout. The success of any future models of healthcare delivery will be reliant of these workers, both to continue in their profession in challenging times and to provide high quality care even in the context of personal challenges.

Finally, beyond the input of mental health professionals in traditional treatment contexts, greater interdisciplinary work is needed in understanding and supporting the psychological determinants of physical health in pandemics. This includes psychological and social models of safety and health behaviours to minimise contagion. This holisitic approach to improving mental and physical health during pandemics will be critical to reducing the risk and effects of any future viral outbreaks.

The health and psychological treatment landscapes have changed substantially as a result of the COVID-19 pandemic. What is clear from these changes, is that flexible, person centred, holistic, and cost effective treatment approaches will be needed now and into the future. Digital technologies will likely prove critical in meeting these needs, although will require careful implementation and training in order to be successful. However, should this be achieved, the capacity for health systems to improve population mental health and be adequately prepared for any future pandemics is certainly cause for considerable hope and optimism.

References

1. The Lancet Infectious Diseases: The intersection of COVID-19 and mental health. Lancet Infect. Dis. **20**(11), 1217 (2020). https://doi.org/10.1016/S1473-3099(20)30797-0
2. Fairburn, C.G., Patel, V.: The impact of digital technology on psychological treatments and their dissemination. Behav. Res. Ther. **88**, 19–25 (2017)
3. Pierce, M., Hope, H., Ford, T., Hatch, S., Hotopf, M., John, A., et al.: Mental health before and during the COVID-19 pandemic: a longitudinal probability sample survey of the UK population. Lancet Psychiatry **7**(10), 883–892 (2020). https://doi.org/10.1016/S2215-0366(20)30308-4
4. Xiong, J., Lipsitz, O., Nasri, F., Lui, L.M.W., Gill, H., Phan, L., et al.: Impact of COVID-19 pandemic on mental health in the general population: a systematic review. J. Affect. Disord. **277**, 55–64 (2020). https://doi.org/10.1016/j.jad.2020.08.001
5. Mohammed, A., Sheikh, T.L., Poggensee, G., Nguku, P., Olayinka, A., Ohuabunwo, C., et al.: Mental health in emergency response: lessons from Ebola. Lancet Psychiatry **2**(11), 955–957 (2015). https://doi.org/10.1016/S2215-0366(15)00451-4
6. Rogers, J.P., Chesney, E., Oliver, D., Pollak, T.A., McGuire, P., Fusar-Poli, P., et al.: Psychiatric and neuropsychiatric presentations associated with severe coronavirus infections: a systematic review and meta-analysis with comparison to the COVID-19 pandemic. Lancet Psychiatry **7**(7), 611–627 (2020). https://doi.org/10.1016/S2215-0366(20)30203-0
7. Roy, A., Singh, A.K., Mishra, S., Chinnadurai, A., Mitra, A., Bakshi, O.: Mental health implications of COVID-19 pandemic and its response in India. Int. J. Soc. Psychiatry **67**(5), 587 (2021)
8. Iqbal, S.Z., Li, B., Onigu-Otito, E., Naqvi, M.F., Shah, A.A.: The long-term mental health effects of COVID-19. Psychiatr. Ann. **50**(12), 522–525 (2020)
9. Wind, T.R., Rijkeboer, M., Andersson, G., Riper, H.: The COVID-19 pandemic: the 'black swan' for mental health care and a turning point for e-health. Internet Interv. **20**, (2020)
10. Kadir, M.A.: Role of telemedicine in healthcare during COVID-19 pandemic in developing countries. Telehealth Med. Today (2020)
11. UNESCO: Education: from disruption to recovery. https://en.unesco.org/covid19/educationresponse (2021). Accessed May 22 2021
12. Lee, J.: Mental health effects of school closures during COVID-19. Lancet Child Adolesc. Health **4**(6), 421 (2020)
13. Kontoangelos, K., Economou, M., Papageorgiou, C.: Mental health effects of COVID-19 pandemia: a review of clinical and psychological traits. Psychiatry Investig. **17**(6), 491 (2020)
14. World Health Organisation: The Impact of COVID-19 on Mental, Neurological and Substance Use Services: Results of Rapid Assessment. Geneva, Switzerland (2020)
15. Smith, K., Bhui, K., Cipriani, A.: COVID-19, Mental Health and Ethnic Minorities. Royal College of Psychiatrists (2020)
16. Clough, B.A., Casey, L.M.: The smart therapist: a look to the future of smartphones and mhealth technologies in psychotherapy. Prof. Psychol.: Res. Pract. (2015). https://doi.org/10.1037/pro0000011
17. Clough, B.A., Rowland, D.P., Casey, L.M.: Development of the eTAP-T: a measure of mental health professionals' attitudes and process towards e-interventions. Internet Interv. **18**, 100288 (2019)

18. Clough, B.A., Casey, L.M.: Technological adjuncts to enhance current psychotherapy practices: a review. Clin. Psychol. Rev. **31**(3), 279–292 (2011). https://doi.org/10.1016/j.cpr.2011.03.006
19. Bueno-Notivol, J., Gracia-García, P., Olaya, B., Lasheras, I., López-Antón, R., Santabárbara, J.: Prevalence of depression during the COVID-19 outbreak: a meta-analysis of community-based studies. Int. J. Clin. Health Psychol. **21**(1), 100196 (2021)
20. Hao, F., Tan, W., Jiang, L., Zhang, L., Zhao, X., Zou, Y., et al.: Do psychiatric patients experience more psychiatric symptoms during COVID-19 pandemic and lockdown? A case-control study with service and research implications for immunopsychiatry. Brain Behav. Immun. **87**, 100–106 (2020)
21. Liu, C.H., Zhang, E., Wong, G.T.F., Hyun, S.: Factors associated with depression, anxiety, and PTSD symptomatology during the COVID-19 pandemic: clinical implications for US young adult mental health. Psychiatry Res. **290**, 113172 (2020)
22. Li, Y., Scherer, N., Felix, L., Kuper, H.: Prevalence of depression, anxiety and post-traumatic stress disorder in health care workers during the COVID-19 pandemic: a systematic review and meta-analysis. PLoS ONE **16**(3), e0246454 (2021)
23. Salehi, M., Amanat, M., Mohammadi, M., Salmanian, M., Rezaei, N., Saghazadeh, A., et al.: The prevalence of post-traumatic stress disorder related symptoms in Coronavirus outbreaks: a systematic-review and meta-analysis. J. Affect. Disord. (2021)
24. Mak, I.W.C., Chu, C.M., Pan, P.C., Yiu, M.G.C., Ho, S.C., Chan, V.L.: Risk factors for chronic post-traumatic stress disorder (PTSD) in SARS survivors. Gen. Hosp. Psychiatry **32**(6), 590–598 (2010)
25. Wang, G., Wang, L., Liu, X., Ning, Y., Hao, W.: The challenge and response of mental health institutions in COVID-19 pandemic: from chaos to new normal. Transl. Psychiatry **10**(1), 1–3 (2020)
26. Xiang, Y.-T., Yang, Y., Li, W., Zhang, L., Zhang, Q., Cheung, T., et al.: Timely mental health care for the 2019 novel coronavirus outbreak is urgently needed. Lancet Psychiatry **7**(3), 228–229 (2020)
27. Sun, S., Goldberg, S.B., Lin, D., Qiao, S., Operario, D.: Psychiatric symptoms, risk, and protective factors among university students in quarantine during the COVID-19 pandemic in China. Glob. Health **17**(1), 1–14 (2021)
28. Charles, N.E., Strong, S.J., Burns, L.C., Bullerjahn, M.R., Serafine, K.M.: Increased mood disorder symptoms, perceived stress, and alcohol use among college students during the COVID-19 pandemic. Psychiatry Res. **296**, 113706 (2021)
29. Yuan, K., Gong, Y.-M., Liu, L., Sun, Y.-K., Tian, S.-S., Wang, Y.-J., et al.: Prevalence of posttraumatic stress disorder after infectious disease pandemics in the twenty-first century, including COVID-19: a meta-analysis and systematic review. Mol. Psychiatry 1–17 (2021)
30. Taquet, M., Luciano, S., Geddes, J.R., Harrison, P.J.: Bidirectional associations between COVID-19 and psychiatric disorder: retrospective cohort studies of 62 354 COVID-19 cases in the USA. Lancet Psychiatry **8**(2), 130–140 (2021)
31. Marvaldi, M., Mallet, J., Dubertret, C., Moro, M.R., Guessoum, S.B.: Anxiety, depression, trauma-related, and sleep disorders among healthcare workers duirng the COVID-19 pandemic: a systematic review and meta-analysis. Neurosci. Biobehav. Rev. (2021)
32. Yao, H., Chen, J.-H., Xu, Y.-F.: Patients with mental health disorders in the COVID-19 epidemic (2020)
33. Jefsen, O.H., Rohde, C., Nørremark, B., Østergaard, S.D.: Editorial perspective: COVID-19 pandemic-related psychopathology in children and adolescents with mental illness. J. Child Psychol. Psychiatry **62**(6), 798–800 (2021)
34. Asmundson, G.J., Paluszek, M.M., Landry, C.A., Rachor, G.S., McKay, D., Taylor, S.: Do pre-existing anxiety-related and mood disorders differentially impact COVID-19 stress responses and coping? J. Anxiety Disord. **74**, 102271 (2020)
35. Zhao, X., Shi, W., Li, X., Li, W., Li, C.: Autistic traits and negative emotions in the general population during COVID-19: mediating roles of the behavioural immune system and COVID-19 risk perception. Psychiatry Res. **300**, 113918 (2021)

36. Degnan, A., Berry, K., Sweet, D., Abel, K., Crossley, N., Edge, D.: Social networks and symptomatic and functional outcomes in schizophrenia: a systematic review and meta-analysis. Soc. Psychiatry Psychiatr. Epidemiol. **53**(9), 873–888 (2018)
37. Corrigan, P.W., Phelan, S.M.: Social support and recovery in people with serious mental illnesses. Community Ment. Health J. **40**(6), 513–523 (2004)
38. Kozloff, N., Mulsant, B.H., Stergiopoulos, V., Voineskos, A.N.: The COVID-19 global pandemic: implications for people with schizophrenia and related disorders. Schizophr. Bull. **46**(4), 752–757 (2020)
39. Maguire, P.A., Reay, R.E., Looi, J.C.: Nothing to sneeze at–uptake of protective measures against an influenza pandemic by people with schizophrenia: willingness and perceived barriers. Australas. Psychiatry **27**(2), 171–178 (2019)
40. Davide, P., Andrea, P., Martina, O., Andrea, E., Davide, D., Mario, A.: The impact of the COVID-19 pandemic on patients with OCD: effects of contamination symptoms and remission state before the quarantine in a preliminary naturalistic study. Psychiatry Res. **291**, 113213 (2020)
41. Stefana, A., Youngstrom, E.A., Jun, C., Hinshaw, S., Maxwell, V., Michalak, E., et al.: The COVID-19 pandemic is a crisis and opportunity for bipolar disorder. Bipolar Disord. **22**(6), 641–643 (2020)
42. Melegari, M., Giallonardo, M., Sacco, R., Marcucci, L., Orecchio, S., Bruni, O.: Identifying the impact of the confinement of Covid-19 on emotional-mood and behavioural dimensions in children and adolescents with attention deficit hyperactivity disorder (ADHD). Psychiatry Res. **296**, 113692 (2021)
43. Fegert, J.M., Vitiello, B., Plener, P.L., Clemens, V.: Challenges and burden of the Coronavirus 2019 (COVID-19) pandemic for child and adolescent mental health: a narrative review to highlight clinical and research needs in the acute phase and the long return to normality. Child Adolesc. Psychiatry Ment. Health **14**, 1–11 (2020)
44. Seppälä, P., Vornanen, R., Toikko, T.: Are children with a number of disabilities and long-term illnesses at increased risk of mental violence, disciplinary violence, and serious violence? J. Interpers. Violence 0886260519898440 (2020)
45. Elbay, R.Y., Kurtulmuş, A., Arpacıoğlu, S., Karadere, E.: Depression, anxiety, stress levels of physicians and associated factors in Covid-19 pandemics. Psychiatry Res. **290**, 113130 (2020)
46. De Kock, J.H., Latham, H.A., Leslie, S.J., Grindle, M., Munoz, S.-A., Ellis, L., et al.: A rapid review of the impact of COVID-19 on the mental health of healthcare workers: implications for supporting psychological well-being. BMC Public Health **21**(1), 1–18 (2021)
47. Dolev, T., Zubedat, S., Brand, Z., Bloch, B., Mader, E., Blondheim, O., et al.: Physiological parameters of mental health predict the emergence of post-traumatic stress symptoms in physicians treating COVID-19 patients. Transl. Psychiatry **11**(1), 1–9 (2021)
48. Kong, X., Cao, Y., Luo, X., He, L.: The correlation analysis between the appearance anxiety and personality traits of the medical staff on nasal and facial pressure ulcers during the novel coronavirus disease 2019 outbreak. Nurs. Open **8**(1), 147–155 (2021)
49. Kang, L., Ma, S., Chen, M., Yang, J., Wang, Y., Li, R., et al.: Impact on mental health and perceptions of psychological care among medical and nursing staff in Wuhan during the 2019 novel coronavirus disease outbreak: A cross-sectional study. Brain Behav. Immun. **87**, 11–17 (2020)
50. Lai, J., Ma, S., Wang, Y., Cai, Z., Hu, J., Wei, N., et al.: Factors associated with mental health outcomes among health care workers exposed to coronavirus disease 2019. JAMA Netw. Open **3**(3), e203976 (2020)
51. Galbraith, N., Boyda, D., McFeeters, D., Hassan, T.: The mental health of doctors during the COVID-19 pandemic. BJPsych Bull. **45**(2), 93–97 (2021)
52. Sahebi, A., Nejati, B., Moayedi, S., Yousefi, K., Torres, M., Golitaleb, M.: The prevalence of anxiety and depression among healthcare workers during the COVID-19 pandemic: an umbrella review of meta-analyses. Prog. Neuro-Psychopharmacol. Biol. Psychiatry 110247 (2021)

53. Liu, Y., Chen, H., Zhang, N., Wang, X., Fan, Q., Zhang, Y., et al.: Anxiety and depression symptoms of medical staff under COVID-19 epidemic in China. J. Affect. Disord. **278**, 144–148 (2021)
54. Bassi, M., Negri, L., Delle Fave, A., Accardi, R.: The relationship between post-traumatic stress and positive mental health symptoms among health workers during COVID-19 pandemic in Lombardy, Italy. J. Affect. Disord. **280**, 1–6 (2021)
55. Clough, B.A., March, S., Chan, R.J., Casey, L.M., Phillips, R., Ireland, M.J.: Psychosocial interventions for managing occupational stress and burnout among medical doctors: a systematic review. Syst. Rev. **6**(1), 1–19 (2017)
56. Sprang, G., Silman, M.: Posttraumatic stress disorder in parents and youth after health-related disasters. Disaster Med. Public Health Prep. **7**(1), 105–110 (2013)
57. Liu, J.J., Bao, Y., Huang, X., Shi, J., Lu, L.: Mental health considerations for children quarantined because of COVID-19. Lancet Child Adolesc. Health **4**(5), 347–349 (2020)
58. Loades, M.E., Chatburn, E., Higson-Sweeney, N., Reynolds, S., Shafran, R., Brigden, A., et al.: Rapid systematic review: the impact of social isolation and loneliness on the mental health of children and adolescents in the context of COVID-19. J. Am. Acad. Child Adolesc. Psychiatry **59**(11), 1218–1239.e3 (2020)
59. Li, X., Fu, P., Fan, C., Zhu, M., Li, M.: COVID-19 stress and mental health of students in locked-down colleges. Int. J. Environ. Res. Public Health **18**(2), 771 (2021)
60. Kaparounaki, C.K,. Patsali, M.E., Mousa, D.-P.V., Papadopoulou, E.V., Papadopoulou, K.K., Fountoulakis, K.N.: University students’ mental health amidst the COVID-19 quarantine in Greece. Psychiatry Res. **290**, 113111 (2020)
61. Lee, J., Jeong, H.J., Kim, S.: Stress, anxiety, and depression among undergraduate students during the COVID-19 pandemic and their use of mental health services. Innov. High. Educ. 1–20 (2021)
62. Lebel, C., MacKinnon, A., Bagshawe, M., Tomfohr-Madsen, L., Giesbrecht, G.: Elevated depression and anxiety symptoms among pregnant individuals during the COVID-19 pandemic. J. Affect. Disord. **277**, 5–13 (2020)
63. Tomfohr-Madsen, L.M,. Racine, N., Giesbrecht, G.F., Lebel, C., Madigan, S.: Depression and anxiety in pregnancy during COVID-19: a rapid review and meta-analysis. Psychiatry Res. 113912 (2021)
64. Şahan, E., Ünal, S.M., Kırpınar, İ: Can we predict who will be more anxious and depressed in the COVID-19 ward? J. Psychosom. Res. **140**, 110302 (2021)
65. Mazza, M.G., De Lorenzo, R., Conte, C., Poletti, S., Vai, B., Bollettini, I., et al.: Anxiety and depression in COVID-19 survivors: role of inflammatory and clinical predictors. Brain Behav. Immun. **89**, 594–600 (2020)
66. Tarsitani, L., Vassalini, P., Koukopoulos, A., Borrazzo, C., Alessi, F., Di Nicolantonio, C., et al.: Post-traumatic stress disorder among COVID-19 survivors at 3-month follow-up after hospital discharge. J. Gen. Intern. Med. **36**(6), 1702–1707 (2021)
67. Chamberlain, S.R., Grant, J.E., Trender, W., Hellyer, P., Hampshire, A.: Post-traumatic stress disorder symptoms in COVID-19 survivors: online population survey. BJPsych Open **7**(2), (2021)
68. Zhang, J., Lu, H., Zeng, H., Zhang, S., Du, Q., Jiang, T., et al.: The differential psychological distress of populations affected by the COVID-19 pandemic. Brain Behav. Immun. **87**, 49 (2020)
69. Vindegaard, N., Benros, M.E.: COVID-19 pandemic and mental health consequences: systematic review of the current evidence. Brain Behav. Immun. **89**, 531–542 (2020)
70. Lopez-Leon, S., Wegman-Ostrosky, T., Perelman, C., Sepulveda, R., Rebolledo, P.A., Cuapio, A., et al.: More than 50 long-term effects of COVID-19: a systematic review and meta-analysis. Available at SSRN 3769978 (2021)
71. Mohr, D.C., Zhang, M., Schueller, S.M.: Personal sensing: understanding mental health using ubiquitous sensors and machine learning. Annu. Rev. Clin. Psychol. **13**, 23–47 (2017)
72. Hays, R., Henson, P., Wisniewski, H., Hendel, V., Vaidyam, A., Torous, J.: Assessing cognition outside of the clinic: smartphones and sensors for cognitive assessment across diverse psychiatric disorders. Psychiatr. Clin. **42**(4), 611–625 (2019)

73. Luettke, S., Hautzinger, M., Fuhr, K.: E-Health in diagnosis and therapy of mental disorders: will therapists soon become superfluous? Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz **61**(3), 263–270 (2018)
74. Torous, J., Onnela, J., Keshavan, M.: New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. Transl. Psychiatry **7**(3), e1053 (2017)
75. Sorkin, D.H., Janio, E.A., Eikey, E.V., Schneider, M., Davis, K., Schueller, S.M., et al.: Rise in use of digital mental health tools and technologies in the United States during the COVID-19 pandemic: survey study. J. Med. Internet Res. **23**(4), e26994 (2021)
76. Research and Markets: Global Emerging Mental Health Devices and Platforms Market: Analysis and Forecast, 2021–2030. Dublin, Ireland (2021)
77. Mandel, A., Veetil, V.: The economic cost of COVID lockdowns: an out-of-equilibrium analysis. Econ. Disasters Clim. Change **4**(3), 431–451 (2020)
78. The Health Foundation: Spending review 2020: priorities for the NHS, social care and the nation's health. https://www.health.org.uk/publications/long-reads/spending-review-2020 (2020). Accessed July 8 2021
79. Crowley, D., Delargy, I.: A national model of remote care for assessing and providing opioid agonist treatment during the COVID-19 pandemic: a report. Harm Reduct. J. **17**(1), 1–5 (2020)
80. Sahu, P., Mathur, A., Ganesh, A., Nair, S., Chand, P., Murthy, P.: Acceptance of e-consult for substance use disorders during the COVID 19 pandemic: a study from India. Asian J. Psychiatr. **54**, 102451 (2020)
81. Moreland, A., Guille, C., McCauley, J.L.: Increased availability of telehealth mental health and substance abuse treatment for peripartum and postpartum women: a unique opportunity to increase telehealth treatment. J. Subst. Abuse Treat. **123**, 108268 (2021)
82. Berryhill, M.B., Culmer, N., Williams, N., Halli-Tierney, A., Betancourt, A., Roberts, H., et al.: Videoconferencing psychotherapy and depression: a systematic review. Telemed. e-Health **25**(6), 435–446 (2019)
83. Farrell, L.J., Oar, E.L., Waters, A.M., McConnell, H., Tiralongo, E., Garbharran, V., et al.: Brief intensive CBT for pediatric OCD with E-therapy maintenance. J. Anxiety Disord. **42**, 85–94 (2016)
84. Elliman, T.D., Schwalb, M.E., Dolan, D., Brim, W., Adler, A.B.: Brief behavioral treatment for insomnia: treatment schedule and training feasibility in the military. Psychol. Serv. (2021)
85. Högdahl, L., Birgegård, A., Björck, C.: How effective is bibliotherapy-based self-help cognitive behavioral therapy with Internet support in clinical settings? Results from a pilot study. Eat. Weight Disord.-Stud. Anorex., Bulim. Obes. **18**(1), 37–44 (2013)
86. Imlach, F., McKinlay, E., Middleton, L., Kennedy, J., Pledger, M., Russell, L., et al.: Telehealth consultations in general practice during a pandemic lockdown: survey and interviews on patient experiences and preferences. BMC Fam. Pract. **21**(1), 1–14 (2020)
87. Backhaus, A., Agha, Z., Maglione, M.L., Repp, A., Ross, B., Zuest, D., et al.: Videoconferencing psychotherapy: a systematic review. Psychol. Serv. **9**(2), 111 (2012)
88. Norwood, C., Moghaddam, N.G., Malins, S., Sabin-Farrell, R.: Working alliance and outcome effectiveness in videoconferencing psychotherapy: a systematic review and noninferiority meta-analysis. Clin. Psychol. Psychother. **25**(6), 797–808 (2018)
89. Thippaiah, S.M., Harbishettar, V., Kumar, T.M., Pandurangi, A.: Hybrid telepsychiatry: a United States perspective with relevance to India. Indian J. Psychol. Med. **42**(5_Suppl.), 108S–112S (2020)
90. Donaghy, E., Atherton, H., Hammersley, V., McNeilly, H., Bikker, A., Robbins, L., et al.: Acceptability, benefits, and challenges of video consulting: a qualitative study in primary care. Br. J. Gen. Pract. **69**(686), e586–e594 (2019)
91. Greenhalgh, T., Shaw, S., Wherton, J., Vijayaraghavan, S., Morris, J., Bhattacharya, S., et al.: Real-world implementation of video outpatient consultations at macro, meso, and micro levels: mixed-method study. J. Med. Internet Res. **20**(4), e9897 (2018)
92. Castillo, M., Conte, B., Hinkes, S., Mathew, M., Na, C., Norindr, A., et al.: Implementation of a medical student-run telemedicine program for medications for opioid use disorder during the COVID-19 pandemic. Harm Reduct. J. **17**(1), 1–6 (2020)

93. Ding, L., She, Q., Chen, F., Chen, Z., Jiang, M., Huang, H., et al.: The internet hospital plus drug delivery platform for health management during the COVID-19 pandemic: observational study. J. Med. Internet Res. **22**(8), e19678 (2020)
94. Clark, S.A., Davis, C., Wightman, R.S., Wunsch, C., Keeler, L.A.J., Reddy, N., et al.: Using telehealth to improve buprenorphine access during and after COVID-19: a rapid response initiative in Rhode Island. J. Subst. Abuse Treat. **124**, 108283 (2021)
95. Thair, H., Holloway, A.L., Newport, R., Smith, A.D.: Transcranial direct current stimulation (tDCS): a beginner's guide for design and implementation. Front. Neurosci. **11**, 641 (2017)
96. Alonzo, A., Fong, J., Ball, N., Martin, D., Chand, N., Loo, C.: Pilot trial of home-administered transcranial direct current stimulation for the treatment of depression. J. Affect. Disord. **252**, 475–483 (2019)
97. Park, J., Oh, Y., Chung, K., Kim, K.J., Kim, C.O., Park, J.Y.: Effect of home-based transcranial direct current stimulation (tDCS) on cognitive function in patients with mild cognitive impairment: a study protocol for a randomized, double-blind, cross-over study. Trials **20**(1), 1–9 (2019)
98. Harrer, M., Adam, S.H., Baumeister, H., Cuijpers, P., Karyotaki, E., Auerbach, R.P., et al.: Internet interventions for mental health in university students: a systematic review and meta-analysis. Int. J. Methods Psychiatr. Res. **28**(2), e1759 (2019)
99. Wildeboer, G., Kelders, S.M., van Gemert-Pijnen, J.E.: The relationship between persuasive technology principles, adherence and effect of web-based interventions for mental health: a meta-analysis. Int. J. Med. Inform. **96**, 71–85 (2016)
100. Christensen, H., Hickie, I.B.: E-mental health: a new era in delivery of mental health services. Med. J. Aust. **192**(11), S2 (2010)
101. Seppala, J., De Vita, I., Miettunen, J., Isohanni, M., Rubinstein, K., Feldman, Y., et al.: Mobile phone and wearable sensor-based mHealth approach for psychiatric disorders and symptoms: systematic review and link to the m-RESIST project. JMIR Ment. Health (2019)
102. Shiffman, S., Stone, A.A., Hufford, M.R.: Ecological momentary assessment. Annu. Rev. Clin. Psychol. **4**, 1–32 (2008)
103. Bell, I.H., Lim, M.H., Rossell, S.L., Thomas, N.: Ecological momentary assessment and intervention in the treatment of psychotic disorders: a systematic review. Psychiatr. Serv. **68**(11), 1172–1181 (2017)
104. Torous, J., Staples, P., Barnett, I., Sandoval, L.R., Keshavan, M., Onnela, J.-P.: Characterizing the clinical relevance of digital phenotyping data quality with applications to a cohort with schizophrenia. NPJ Digit. Med. **1**(1), 1–9 (2018)
105. Depp, C.A., Moore, R.C., Perivoliotis, D., Granholm, E.: Technology to assess and support self-management in serious mental illness. Dialogues Clin. Neurosci. **18**(2), 171 (2016)
106. Kleiman, E.M., Yeager, A.L., Grove, J.L., Kellerman, J.K., Kim, J.S.: Real-time mental health impact of the COVID-19 pandemic on college students: ecological momentary assessment study. JMIR Ment. Health **7**(12), e24815 (2020)
107. Dagum, P.: Digital biomarkers of cognitive function. NPJ Digit. Med. **1**(1), 1–3 (2018)
108. Reinertsen, E., Clifford, G.D.: A review of physiological and behavioral monitoring with digital sensors for neuropsychiatric illnesses. Physiol. Meas. **39**(5), 05TR1 (2018)
109. Huckvale, K., Venkatesh, S., Christensen, H.: Toward clinical digital phenotyping: a timely opportunity to consider purpose, quality, and safety. NPJ Digit. Med. **2**(1), 1–11 (2019)
110. Hull, T.D., Levine, J., Bantilan, N., Desai, A.N., Majumder, M.S.: Analyzing digital evidence from a telemental health platform to assess complex psychological responses to the COVID-19 pandemic: content analysis of text messages. JMIR Form. Res. **5**(2), e26190 (2021)
111. Jagesar, R.R., Roozen, M.C., van der Heijden, I., Ikani, N., Tyborowska, A., Penninx, B.W., et al.: Digital phenotyping and the COVID-19 pandemic: capturing behavioral change in patients with psychiatric disorders. Eur. Neuropsychopharmacol. **42**, 115–120 (2021)
112. Henson, P., D'Mello, R., Vaidyam, A., Keshavan, M., Torous, J.: Anomaly detection to predict relapse risk in schizophrenia. Transl. Psychiatry **11**(1), 1–6 (2021)
113. Grossman, Z., Chodick, G., Reingold, S.M., Chapnick, G., Ashkenazi, S.: The future of telemedicine visits after COVID-19: perceptions of primary care pediatricians. Isr. J. Health Policy Res. **9**(1), 1–10 (2020)

114. Harris, D.A., Archbald-Pannone, L., Kaur, J., Cattell-Gordon, D., Rheuban, K.S., Ombres, R.L., et al.: Rapid telehealth-centered response to COVID-19 outbreaks in postacute and long-term care facilities. Telemed. e-Health **27**(1), 102–106 (2021)
115. Graham, A.K., Lattie, E.G., Powell, B.J., Lyon, A.R., Smith, J.D., Schueller, S.M., et al.: Implementation strategies for digital mental health interventions in health care settings. Am. Psychol. **75**(8), 1080 (2020)
116. Australian Government Department of Health: PHN Mental Health Flexible Funding Pool Programme Guidance: Stepped Care. Canberra, Australia (2019)
117. Bower, P., Gilbody, S.: Stepped care in psychological therapies: access, effectiveness and efficiency: narrative literature review. Br. J. Psychiatry **186**(1), 11–17 (2005)
118. Anderson, J., Proudfoot, J., Gale, N., Christensen, H., Reeves, P., O'Moore, K.: Implementation and cost effectiveness evaluation of an integrated mental health stepped care service for adults in primary care. Int. J. Integr. Care (IJIC) **19**, (2019)
119. Chatterton, M.L., Rapee, R.M., Catchpool, M., Lyneham, H.J., Wuthrich, V., Hudson, J.L., et al.: Economic evaluation of stepped care for the management of childhood anxiety disorders: results from a randomised trial. Aust. N. Z. J. Psychiatry **53**(7), 673–682 (2019)
120. Stiles, J.A,. Chatterton, M.L,. Le, L.K.-D., Lee, Y.Y., Whiteford, H., Mihalopoulos, C.: The cost-effectiveness of stepped care for the treatment of anxiety disorders in adults: a model-based economic analysis for the Australian setting. J. Psychosom. Res. **125**, 109812 (2019)
121. Frasquilho, D., Matias, R., Grácio, J., Sousa, B., Luís-Ferreira, F., Leal, J., et al.: Protocol for the implementation and assessment of "MoodUP": a stepped care model assisted by a digital platform to accelerate access to mental health care for cancer patients amid the COVID-19 pandemic. Int. J. Environ. Res. Public Health **18**(9), 4629 (2021)
122. Orman, J., O'Dea, B.: e-Therapy in primary care mental health. Aust. J. Gen. Pract. (2018)
123. Meuldijk, D., Wuthrich, V.M., Rapee, R.M., Draper, B., Brodaty, H., Cuijpers, P., et al.: Translating evidence-based psychological interventions for older adults with depression and anxiety into public and private mental health settings using a stepped care framework: study protocol. Contemp. Clin. Trials **104**, 106360 (2021)
124. Sturk, H., Crowther, R., Kavanagh, D.J.: Head to health: practitioner perceptions of the new digital mental health gateway. Aust. J. Rural Health **27**(5), 448–453 (2019)
125. Australian Indigenous Health InfoNet: WellMob. https://wellmob.org.au/ (2021). Accessed July 8 2021
126. Taylor, C.B., Fitzsimmons-Craft, E.E., Graham, A.K.: Digital technology can revolutionize mental health services delivery: the COVID-19 crisis as a catalyst for change. Int. J. Eat. Disord. **53**(7), 1155–1157 (2020)
127. Torous, J., Myrick, K.J., Rauseo-Ricupero, N., Firth, J.: Digital mental health and COVID-19: using technology today to accelerate the curve on access and quality tomorrow. JMIR Ment. Health **7**(3), e18848 (2020)
128. Corruble, E.: A viewpoint from Paris on the COVID-19 pandemic: a necessary turn to telepsychiatry. J. Clin. Psychiatry **81**(3), (2020)
129. Fagiolini, A., Cuomo, A., Frank, E.: COVID-19 diary from a psychiatry department in Italy. J. Clin. Psychiatry **81**(3), (2020)
130. Topooco, N., Riper, H., Araya, R., Berking, M., Brunn, M., Chevreul, K., et al.: Attitudes towards digital treatment for depression: a European stakeholder survey. Internet Interv. **8**, 1–9 (2017)
131. Gibson, K., O'Donnell, S., Coulson, H., Kakepetum-Schultz, T.: Mental health professionals' perspectives of telemental health with remote and rural First Nations communities. J. Telemed. Telecare **17**(5), 263–267 (2011)
132. Bennett-Levy, J., Singer, J., DuBois, S., Hyde, K.: Translating e-mental health into practice: what are the barriers and enablers to e-mental health implementation by Aboriginal and Torres Strait Islander health professionals? J. Med. Internet Res. **19**(1), e1 (2017)
133. Haberstroh, S., Parr, G., Bradley, L., Morgan-Fleming, B., Gee, R.: Facilitating online counseling: perspectives from counselors in training. J. Couns. Dev. **86**(4), 460–470 (2008)

134. Sinclair, C., Holloway, K., Riley, G., Auret, K.: Online mental health resources in rural Australia: clinician perceptions of acceptability. J. Med. Internet Res. **15**(9), e193 (2013)
135. Australian Psychological Society: The APS Response to teh Productivity Commission Inquiry into Mental Health. Melbourne, Australia (2019)
136. Bucci, S., Schwannauer, M., Berry, N.: The digital revolution and its impact on mental health care. Psychol. Psychother. Theory Res. Pract. **92**(2), 277–297 (2019)
137. Drude, K.P., Hertlien, K.M., Maheu, M.M., Hilty, D.M., Wall, K.: Telebehavioral health competencies in interprofessional education and training: a pathway to interprofessional practice. J. Technol. Behav. Sci. **5**(1), 30–39 (2020)
138. Callens, S.: The EU Legal Framework on E-health. European Observatory on Health Systems and Policies en l'Observatoire Social … (2010)
139. Maheu, M.M., Drude, K.P., Hertlein, K.M., Lipschutz, R., Wall, K., Hilty, D.M.: An interprofessional framework for telebehavioral health competencies. J. Technol. Behav. Sci. **2**(3–4), 190–210 (2017)
140. Maslach, C., Jackson, S.E., Leiter, M.P., Schaufeli, W.B., Schwab, R.L.: Maslach Burnout Inventory. Consulting Psychologists Press, Palo Alto CA (1986)
141. Greenberg, N., Docherty, M., Gnanapragasam, S., Wessely, S.: Managing mental health challenges faced by healthcare workers during covid-19 pandemic. bmj **368**, (2020)
142. Ibar, C., Fortuna, F., Gonzalez, D., Jamardo, J., Jacobsen, D., Pugliese, L., et al.: Evaluation of stress, burnout and hair cortisol levels in health workers at a University Hospital during COVID-19 pandemic. Psychoneuroendocrinology **128**, 105213 (2021)
143. Clough, B.A., March, S., Leane, S., Ireland, M.J.: What prevents doctors from seeking help for stress and burnout? A mixed-methods investigation among metropolitan and regional-based Australian doctors. J. Clin. Psychol. **75**(3), 418–432 (2019)
144. Clough, B.A., Hill, M., Delaney, M., Casey, L.M.: Development of a measure of stigma towards occupational stress for mental health professionals. Soc. Psychiatry Psychiatr. Epidemiol. **55**(7), 941–951 (2020)
145. Clough, B.A., Ireland, M.J., March, S.: Development of the SOSS-D: a scale to measure stigma of occupational stress and burnout in medical doctors. J. Ment. Health **28**(1), 26–33 (2019)
146. Yang, L., Yin, J., Wang, D., Rahman, A., Li, X.: Urgent need to develop evidence-based self-help interventions for mental health of healthcare workers in COVID-19 pandemic. Psychol. Med. 1–2 (2020)
147. Freedland, K.E., Dew, M.A., Sarwer, D.B., Burg, M.M., Hart, T.A., Ewing, S.W.F., et al.: Health psychology in the time of COVID-19 (2020)
148. Centers for Disease Control and Prevention: Guidance for unvaccinated people: how to protect yourself and others. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html (2021). Accessed July 4th 2021
149. Rossi, R., Socci, V., Talevi, D., Mensi, S., Niolu, C,. Pacitti, F., et al.: COVID-19 pandemic and lockdown measures impact on mental health among the general population in Italy. Front. Psychiatry **11**(790), (2020). https://doi.org/10.3389/fpsyt.2020.00790
150. Niedzwiedz, C.L., Green, M.J., Benzeval, M., Campbell, D., Craig, P., Demou, E., et al.: Mental health and health behaviours before and during the initial phase of the COVID-19 lockdown: longitudinal analyses of the UK Household Longitudinal Study. J. Epidemiol. Community Health **75**(3), 224–231 (2021)
151. Adams-Prassl, A., Boneva, T., Golin, M., Rauh, C.: The impact of the coronavirus lockdown on mental health: evidence from the US (2020)
152. Hagger, M.S., Smith, S.R., Keech, J.J., Moyers, S.A., Hamilton, K.: Predicting social distancing intention and behavior during the COVID-19 pandemic: an integrated social cognition model. Ann. Behav. Med. **54**(10), 713–727 (2020)
153. Hamilton, K., Smith, S.R., Keech, J.J., Moyers, S.A., Hagger, M.S.: Application of the health action process approach to social distancing behavior during covid-19. Appl. Psychol. Health Well Being **12**(4), 1244–1269 (2020)

154. Lin, C.Y., Imani, V., Majd, N.R., Ghasemi, Z., Griffiths, M.D., Hamilton, K., et al.: Using an integrated social cognition model to predict COVID-19 preventive behaviours. Br. J. Health Psychol. **25**(4), 981–1005 (2020)
155. Hagger, M.S., Smith, S.R., Keech, J.J., Moyers, S.A., Hamilton, K.: Predicting physical distancing over time during COVID-19: testing an integrated model. Psychol. Health (2021). https://doi.org/10.1080/08870446.2021.1968397
156. Reyes Fernández, B., Knoll, N., Hamilton, K., Schwarzer, R.: Social-cognitive antecedents of hand washing: action control bridges the planning–behaviour gap. Psychol. Health **31**(8), 993–1004 (2016)
157. Zhang, C.-Q., Fang, R., Zhang, R., Hagger, M.S., Hamilton, K.: Predicting hand washing and sleep hygiene behaviors among college students: test of an integrated social-cognition model. Int. J. Environ. Res. Public Health **17**(4), 1209 (2020)
158. Zhang, C.-Q., Chung, P.-K., Liu, J.-D., Chan, D.K., Hagger, M.S., Hamilton, K.: Health beliefs of wearing facemasks for influenza A/H1N1 prevention: a qualitative investigation of Hong Kong older adults. Asia Pac. J. Public Health **31**(3), 246–256 (2019)
159. Smith, S.R., Hagger, M.S., Keech, J.J., Moyers, S.A., Hamilton, K.: Improving hand hygiene behavior using a novel theory-based intervention during the COVID-19 pandemic. J. Exp. Psychol.: Appl. (under review)
160. Widmer, R.J., Collins, N.M., Collins, C.S., West, C.P., Lerman, L.O., Lerman, A.: Digital health interventions for the prevention of cardiovascular disease: a systematic review and meta-analysis. Mayo Clin. Proc. **90**(4), 469–480 (2015). https://doi.org/10.1016/j.mayocp.2014.12.026
161. Howarth, A., Quesada, J., Silva, J., Judycki, S., Mills, P.R.: The impact of digital health interventions on health-related outcomes in the workplace: a systematic review. Digit. Health **4**, 2055207618770861 (2018)
162. Neville, L.M., O'Hara, B., Milat, A.: Computer-tailored physical activity behavior change interventions targeting adults: a systematic review. Int. J. Behav. Nutr. Phys. Act. **6**(1), 30 (2009). https://doi.org/10.1186/1479-5868-6-30
163. Yardley, L., Spring, B.J., Riper, H., Morrison, L.G., Crane, D.H., Curtis, K., et al.: Understanding and promoting effective engagement with digital behavior change interventions. Am. J. Prev. Med. **51**(5), 833–842 (2016). https://doi.org/10.1016/j.amepre.2016.06.015
164. Penedo, F.J., Dahn, J.R.: Exercise and well-being: a review of mental and physical health benefits associated with physical activity. Curr. Opin. Psychiatry **18**(2), 189–193 (2005)
165. Jane-Llopis, E., Matytsina, I.: Mental health and alcohol, drugs and tobacco: a review of the comorbidity between mental disorders and the use of alcohol, tobacco and illicit drugs. Drug Alcohol Rev. **25**(6), 515–536 (2006). https://doi.org/10.1080/09595230600944461

Innovations in Surgery—How Advances in the Delivery of Surgical Care and Training Can Help Hospitals Recover from COVID-19

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Abstract There has been a significant reduction in elective surgical activity since the start of the COVID-19 pandemic. As a consequence, record numbers of patients are awaiting planned procedures. Furthermore, surgical trainees the world over have been deprived of vital operative experience. In this chapter we explore how adoption of technological innovations might help to reduce the backlog of unmet surgical care. We examine how the shortfall in surgical training could be mitigated through technology-enhanced learning (TEL) by using extended reality (XR) technologies. High fidelity XR surgical simulation has exciting applications in pre-operative planning, acquisition and assessment of surgical skills and surgical telementoring. In addition, artificial intelligence (AI) technology is expected to have an increasingly prominent role in healthcare in the near future. Increasing automation of laborious tasks using AI could enhance efficiency of surgical care whilst freeing up more time for trainees to focus on becoming better surgeons. This chapter presents specific examples of how TEL, XR and AI technologies can be used to train surgeons and improve the care of surgical patients. These technologies, if implemented in a robust, expeditious manner, may provide the radical solutions needed for healthcare systems to begin the recovery from a global pandemic.

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1 Introduction

In 2020 an estimated 28.4 million elective surgical procedures worldwide were postponed or cancelled to free up hospital capacity to treat patients with coronavirus disease 2019 (COVID-19) [1]. Meanwhile, an unprecedented backlog of patients awaiting elective procedures and outpatient appointments has accumulated. As of April 2021, there were a staggering 5.1 million patients awaiting elective specialist treatment in the England [2]. Intriguingly, referrals for specialist care in England were down by 4.7 million during the first wave, between January to August 2020 compared to the same period in 2019 [3]. It is implausible that demand for specialist intervention had reduced during this period. Rather, it suggests there may be a 'hidden backlog' of unmet care which will likely rebound, resulting in even more referrals over time. The second wave of the COVID-19 pandemic has caused further cancellations to elective surgery in the UK. Protracted waiting times for clinics and surgery have resulted in increased patient morbidity and excess deaths [4]. In addition, reduced elective operating volume has had a significant impact on the training of the surgeons of tomorrow. Large, complex challenges require radical solutions. We wish to offer our perspective on innovations that can assist the recovery of surgical care and training as we emerge from the global pandemic. We will present specific examples of how technology enhanced learning (TEL), extended reality (XR) technologies and artificial intelligence (AI) can be deployed to improve surgical care and surgical training.

2 Innovations in Surgical Care

2.1 Remote Ward Rounds

Extended reality (XR) technologies have been trialled during the COVID-19 pandemic to allow doctors to care for patients remotely. XR encompasses virtual reality (VR), augmented reality (AR) and mixed reality (MR). In this section AR and MR will be discussed in more depth given their potential uses in a live clinical environment. Applications of VR will be discussed in greater detail in the "Innovations in surgical training" section.

Augmented reality (AR) has been thrust into the mainstream by smartphone games and social media platforms such as Pokemon Go™, Instagram™ and Snapchat™ [5]. AR is achieved by superimposing digital information on to a live view of the real world captured using a video camera. This digital information can be overlaid on to a smartphone screen, endoscopy monitor or a wearable device such as

Google Glass™. Users can visualise (but cannot manipulate) the augmented information on screen. Mixed reality (MR) takes AR one step further. MR allows users to physically interact with and manipulate digitally rendered holograms which are superimposed onto a view of the real world. Specially designed wearable headsets known as head-mounted displays (HMD) are required to facilitate MR. These can be tethered (requiring a connection to a computer or laptop) or untethered (standalone and wireless). Microsoft's HoloLens™ 2 is a recent example of an untethered MR HMD. Many predict huge investment growth in XR industry in the coming decade, with some analysts predicting a sixfold increase in VR and MR headset purchases by 2025 [6, 7]. An extensive review of the digital future of the National Health Service in the UK (NHS) predicts that by 2040, greater than 80% of the NHS workforce will use XR technology for their day-to-day working [8]. This burgeoning sector offers a multitude of exciting opportunities to modernise surgical care, with many examples to be discussed in this chapter.

Paediatric cardiac surgeons in the UK have piloted MR ward rounds using HoloLens™ 2 and remote assist software [9]. Using the untethered headset, ward rounds were conducted by a single clinician whilst the audio and visual feed was live-streamed to the rest of the team. Two-way communication allowed the remote team to display relevant imaging and blood results directly to the clinician's heads-up display, all whilst keeping the clinician's hands free to interact with and examine patients. Patient records were updated easily and remotely by a junior member of the team. Traditionally, scribing of ward round notes can be an onerous task when writing in large volume paper case notes or having to repeatedly log on to mobile ward laptops to update electronic records during the round. Voice-activated commands for sharing of images and making calls proved useful in scenarios when personal protective equipment (PPE) was required. Minimising the number of clinicians present on ward rounds can reduce risk of infection whilst also reducing PPE usage [9, 10]. One study reported a 52% reduction in the time staff were exposed to COVID-19 and an 83% reduction in PPE usage by using HoloLens™ 2 for MR ward rounds on COVID-19 wards [11]. The use of MR ward rounds can be particularly useful in highly specialised care settings such as paediatric cardiac surgery, where numerous specialists are required to attend the multi-disciplinary round [9]. In the UK, highly specialist services are usually centralised in centres of excellence, based in hospitals in large metropolitan areas. MR technology could facilitate specialists to "attend" ward rounds in rural areas remotely, potentially improving the quality of care and expertise for these patient populations. So far, MR ward rounds have only been trialled in pilot studies. It is clear that there are many exciting potential applications which may warrant rapid adoption of this technology for use in the ward environment in the near future. However, a reduction in patient contact time may diminish learning opportunities for junior clinicians in addition to preventing the development of strong doctor-patient relationships. These factors must be considered when upscaling use of MR technology in the ward environment.

2.2 XR Enhanced Multi-Disciplinary Team Meetings and Pre-Operative Planning

Immersive and interactive MR multidisciplinary team (MDT) meetings have been piloted. A congenital cardiac surgery MDT was conducted with multiple attendees donning HoloLens™ HMDs. All participants were able to visualise virtual, patient-specific 3D anatomical models which were rendered from real patient cardiac magnetic resonance imaging (MRI) data. Participants were able to manipulate and interact with the 3D anatomical model through use of gestures rather than traditional keyboard and mouse. This approach could allow greater visuospatial appreciation of complex cardiac anatomy, which may be particularly beneficial for pre-operative planning [12]. The immersive nature of MR could potentially reduce distraction and improve clinician engagement in MDT discussions, leading to better decision making whilst improving the educational value for junior staff in attendance [13].

2.3 XR Pre-operative Planning and Intra-operative Anatomical Guidance

AR software has been developed to enhance pre-operative planning. One example is a program called OpenSight AR, has received approval from the Food and Drug Administration (FDA) in the USA [14]. It utilises Microsoft HoloLens™ to project patient-specific CT and MRI images directly on to the patient in the form of 3D anatomical holograms. Infrared cameras around the patient track movement, allowing the holograms to accommodate for changes in patient position. So far, this technology has been tested in proof-of-concept studies, where percutaneous pedicle screws were inserted accurately into silicone lumbar spine models by orthopaedic residents without the need for fluoroscopic guidance [15]. This technology has the potential to assist in the optimal placement of surgical incisions and before “knife-to-skin” in open surgery. It may also help with planning of precise instrumentation for percutaneous procedures, endoscope insertion or foreign body removal. So far, pre-operative AR anatomical guidance programs have mainly been piloted in the laboratory by orthopaedic surgeons in artificial physical models [15, 16]. Plastic surgeons have conducted a six-patient case series which utilised AR projected CT angiography images to locate and dissect perforator vessels for pedicled free flaps in live patients, instead of the conventional Doppler probe [17]. They found the AR surface anatomy guidance to be more reliable and less time consuming than using Doppler ultrasound. MR anatomical guidance has been piloted by otolaryngologists in live parotid surgery. The study found that MR anatomical mapping in soft tissue structures with complex anatomy may not yet be sufficiently accurate with the current generation of MR technology [16]. Further in-vivo studies are warranted before increased adoption of this technology in to the live operating theatre environment.

In endoscopic and minimally-invasive surgery, it may be ergonomically advantageous to use MR HMDs to visualise the video feed from the endoscope instead of using traditional monitors. Medical students learnt how to perform ureteric stone removal on a physical model simulator more quickly and with greater competence using a Microsoft HoloLens™ device [18]. The authors postulate that better performance was achieved in the HoloLens™ group due to improved alignment of line of vision and hand placement compared to the use of a conventional monitor. Use of the headsets was well tolerated, with 90% of participants not reporting any negative effects during usage. 97% of the participants felt that MR training with Hololens™ will have a significant role in surgical education in the future [18].

2.4 XR Intra-Operative Telementoring

In the operating theatre, AR operative instructions can be sent by a remote mentor to a mentee wearing an MR HMD. These 3D annotations are then projected onto the mentee's operative field in real time. One study showed how surgical residents performed leg fasciotomies with greater confidence, in less time and with fewer errors when receiving telementoring and AR instructions from an expert surgeon based remotely [19]. Live MR HMD-assisted telementoring could prove useful in difficult operative cases where specific surgical expertise may not be available to attend physically. This is particularly pertinent given the current pandemic situation. Surgeons with underlying health conditions can still offer their expertise remotely whilst 'shielding'. However, data protection and information governance must be carefully considered in the context of live video streaming of surgery.

2.5 The Rising Role of AI in Surgical Care

AI is a field of applied computer science whereby computer algorithms are designed to perform tasks in a manner that usually requires human intelligence [20]. These computer programs can imitate intelligent human behaviour through learning, reasoning and self-correction [21]. AI is expected to transform the delivery of healthcare in the near future. The last few years have seen huge growth in the healthcare AI market, and this is likely to accelerate. Global market size was estimated to be $2.5 billion USD in 2018; this value has been forecast to exceed $31 billion USD by 2025 [22]. The availability of 'big data' in healthcare and declining computer hardware costs are some of the factors driving growth in this sector [22]. In addition, automation of administrative processes have the potential to reduce human resource costs. However, adoption of AI algorithms in healthcare is in its infancy. Fewer than 40 AI programs have so far been adequately trialled and approved by the US Food and Drug Administration (FDA) for safe use in healthcare, mostly in non-surgical specialties such as cardiology and radiology [23, 24]. It is predicted that AI will revolutionise medical and surgical care around the world. However, it is clear that an investment of significant resources is required to develop, validate and importantly implement the applications described later in the chapter.

AI is an umbrella term encompassing various modalities of data processing by computer algorithms.

So far, the most widely utilised AI modality in healthcare has been machine learning. This is an AI technique whereby computer algorithms are trained with large amounts of labelled data during a training period known as supervised learning. The expected outcomes (known as ground truths) are carefully defined by human experts. Following this training phase, the algorithm will subsequently undergo a testing phase. If the algorithm does not produce the desired output, humans can adjust the algorithms and repeat the training accordingly [25]. Alternatively, algorithms can be devised to undergo unsupervised learning, where no labelled data is given to the algorithm. The algorithm analyses the training data more generally and identifies common themes or clusters in the data. During supervised or unsupervised learning phases algorithms can subsequently change their behaviour depending on what it has learned from the data it has been given. If a machine learning algorithm encounters a new problem, it will produce a solution as an approximation based on its prior 'knowledge' acquired during the training phase. This differs from conventional computer programs which utilise rule-based algorithms, whereby data is processed inflexibly within the confines of the rules that have been set by a human programmer [26].

Deep learning is built upon the machine learning concept. Deep learning algorithms process data using so-called deep neural networks. These neural networks consist of multiple interconnected layers of algorithmic processing. Data is inputted at one end and is processed sequentially at each layer, but cross-talk between each layer happens simultaneously, in a way comparable to human brain activity. However, massive amounts of data are required to train a deep learning algorithm, after which the algorithm can classify data into groups without any explicit programming by humans [25, 26]. This AI technique is particularly useful for object recognition and feature extraction from images [25, 27]. Here we present use cases of AI in surgery and explain how they could enhance surgical care and training and assist in the pandemic recovery.

2.6 AI in Clinical Diagnostics

Ophthalmology AI can help clinicians diagnose disease. Deep learning algorithms have been designed to autonomously and accurately analyse and interpret digital images including photographs, plain radiographs and scans. The clinical burden of screening programmes can be significantly reduced with the help of deep learning algorithms. In ophthalmology, one retinal image analysis AI algorithm has been prospectively trialled in the screening of 30,000 UK patients for presence of diabetic retinopathy. The study demonstrated 95.7% sensitivity for detecting retinal damage requiring referral to ophthalmology and 100% sensitivity in diagnosing moderate to severe retinopathy [28]. It reduced screening workload of ophthalmologists by half, which could free up clinician time to address the post-pandemic backlog of elective procedures [28]. Two automated retinal image analysis systems to date have received FDA approval [28, 29]. There is hope that automated screening tools could be used in primary care, facilitating earlier diagnosis and minimising delay to treatments such as retinal laser photocoagulation surgery.

Orthopaedics Deep learning may prove effective in the diagnosis of fractures from radiographs. One deep learning algorithm was better at identifying scaphoid fractures from radiographs than emergency physicians, but not quite as accurate as an experienced orthopaedic surgeon [30]. Another deep learning algorithm has received FDA approval in the US by significantly improving clinician performance in diagnosis of distal radius fractures from radiographs [31]. These diagnostic support tools have the potential to increase speed of diagnosis and reduce the number of missed fractures, thus improving outcomes in the management of fractures.

Otolaryngology Large sub-specialty areas within otolaryngology are beginning to incorporate some degree of AI technology [27]. Liu et all demonstrate the utility of machine learning algorithms in accurately diagnosing endolymphatic hydrops from optical coherence tomography scans in mice [32]. In order to address well known inter-rater variability in the analysis of paranasal sinus CT scans, Chowdhury et al. describe a neural network created to classify cross-sectional sinus imaging [33]. Both examples have shown remarkably positive results in early testing, however demonstration of how this technology actually improves the care of patients is yet to be shown with any confidence.

Oncological Surgery As with retinopathy screening discussed above, radiology-based nationwide cancer screening programmes are likely to benefit greatly by adopting AI algorithms. In the UK and Europe, breast cancer screening requires two radiologists to “double read” the mammograms. Preliminary results from one UK study analysing 40,000 mammograms demonstrated how replacing one of the radiologists with a deep learning algorithm produced equivalent results in breast cancer detection and patient recall rate for further assessment when compared with the traditional double reader screening [34]. Due to the COVID pandemic, it is predicted that one million women in the UK have missed breast cancer screening appointments [35]. AI algorithms may help to reduce this backlog, allowing earlier detection of breast cancers which could expedite surgical intervention for those that require it.

In cancer surgery, intra-operative histopathological analysis is sometimes required to define tumour margins during the surgical resection. Halicek et al. have used novel imaging techniques to rapidly analyse histology specimens. Hyperspectral imaging captures reflected light from specimens which can be used to distinguish benign and malignant lesions. This data was used to train a deep learning algorithm, and the authors demonstrated a greater than 85% accuracy in detecting close or positive tumour margins for head and neck squamous cell carcinoma (SCC) resections

[36]. The hyperspectral imaging analysis takes less than two minutes to complete. Currently, standard practice for intra-operative pathology is through frozen section analysis. In the literature, reported accuracy of SCC detection from frozen sections is between 71 and 92%, but each specimen analysis takes around 25 minutes to report [36]. This novel AI-based technique has the potential to drastically reduce intra-operative pathology consultation time and thus total operating theatre time, whilst maintaining equivalent accuracy.

2.7 AI in Histopathology

AI algorithms have the potential to greatly reduce clinical workload for histopathologists. Increasing adoption of digitised whole slide images of pathology slides could allow pathologists to utilise AI autonomous image recognition capabilities. One study showed how pathologists were able to more accurately and more quickly identify breast cancer micrometastatic deposits in lymph nodes with the assistance of a deep learning algorithm. AI assistance halved the time it took for pathologists to review the slides for metastases, taking 61 seconds versus 117 seconds without AI [37]. Similar algorithms have been studied in urological pathology. Ström et al. studied a deep learning algorithm which was able to detect and grade prostate needle biopsy samples with accuracy equivalent to expert histopathologists [38]. Reduction of urological pathology workload could be particularly valuable given there is a worldwide shortage of prostate pathologists [38]. These examples demonstrate how AI could expedite histopathological diagnosis of suspected cancers. These advances have the potential to streamline the workflow for urgent oncological surgical specialties. More timely diagnosis may allow more timely surgery, thus helping to reduce the surgical backlog that has accrued.

2.8 Current Limitations of AI Technology

There are many barriers to the widespread adoption of AI technologies into the healthcare sector. As a consequence, only a few AI applications have received approval from the regulatory authorities in the developed nations, despite an explosion in interest and investment in the field. Regulatory frameworks must be carefully designed to assess the safety of this new category of medical device. In the USA, the FDA are currently considering a "total product lifecycle-based regulatory framework" which allows ongoing regulation, taking into consideration that algorithm performance may change over time, as it undergoes further training and real-world learning [24]. In the UK, the National Institute for Health Research (NIHR) have established the Artificial Intelligence in Health and Care Award (AI award) to fund promising AI applications. Their aim is to streamline the implementation of these technologies into the NHS whilst allowing independent and transparent evaluation. This could accelerate the adoption of technologies that have been proven to be effective [39]. However, the majority of published studies in AI interventions to date are proof-of-concept or early stage validation studies. More robust clinical trial data is essential before the widespread adoption of AI technologies. Comprehensive consensus guidelines for the reporting of AI-specific clinical trials protocols were recently published [40]. This document will support research teams in conducting rigorous clinical trials and reduce reporting bias in the literature. It may also assist external reviewers critically appraising research studies for AI interventions in healthcare.

Confidentiality and data governance are important considerations. The training of AI algorithms requires vast amounts of data sharing. It is paramount that sensitive patient data be handled and stored safely. Apprehension regarding the 'black box' nature of deep learning algorithms has been previously documented [25]. The convoluted and opaque processing of deep learning algorithms means it can be difficult to ascertain exactly how they arrived at their conclusions. This raises concerns about accountability and liability, which could damage public trust in the healthcare system [41]. These implications need be carefully considered when implementing AI technologies. However, rather than dismissing deep learning algorithms on this basis, it pertinent to remind ourselves that many drug mechanisms of action are poorly understood, yet this does not preclude their usefulness.

3 Innovations in Surgical Training and Technology-Enhanced Learning (TEL)

The pandemic has decimated training opportunities for surgical trainees the world over. An unprecedented backlog of patients requiring elective surgery has accumulated. As we steer our way towards recovery from the pandemic, there will be an even greater emphasis on 'service provision'. Pressure to reduce the backlog through high turnover of elective cases reduces training opportunities further. The NHS is heavily reliant on trainees for unsupervised 'service provision', to the detriment of their training [42]. Diminished training opportunities have forced educators to consider novel methods to facilitate acquisition of surgical knowledge and skills.

Simulation allows trainees to practice scenarios which mimic real life. It is a broad term which encompasses everything from simulated history taking to performing surgical procedures on human cadavers. Simulation is an indispensable part of modern surgical training, and concerted efforts have been made to upscale its use in the UK surgical curricula [42]. More recently, there has been a growing adoption of technology-enhanced learning (TEL) in surgical education. TEL is defined as "the use of technology as a part of the learning process [8]. More specifically, we will discuss virtual reality (VR) and its role in modernising surgical training. AR and MR technologies will be discussed briefly as they have mostly been covered in the previous section.

VR is the creation of an immersive and interactive digital environment, combining visual information in the form of computerised graphics through head mounted displays (HMDs), auditory information through headphones and haptic feedback and interactivity through paired hand controls. It differs from AR and MR in that it is completely immersive—the entire landscape is computer generated, without any view of the real-world environment. Mass adoption of VR technology has historically been held back by unconvincing computer graphics due to low resolution screen technology and inadequate computer processing power. High costs and reports of motion sickness have served as further barriers [43]. However, rapid technological advancements largely adapted from the smartphone sector have given rise to standalone VR HMDs such as the Oculus Quest 2™. These can operate without a wired connection to a PC, allowing portability and unrestricted movement whilst significantly reducing cost. Tethered VR HMDs such as the Valve Index™ are typically more powerful than standalone HMDs, but require a cable connection to a powerful 'gaming' PC. Fast computer processors and next generation graphics cards are essential for smooth operation. These HMDs are widely used in the gaming industry but are now being adopted for medical simulation. More advanced enterprise level HMDs include those developed by Varjo™ and Pico Interactive™. These companies are concentrating on industry use-cases such as product design, engineering and flight simulation. These systems use state-of-the-art computing to maximise fidelity and therefore carry higher cost.

3.1 Acquisition of Surgical Skills

VR training is particularly useful for junior surgeons acquiring new surgical skills [44, 45]. A recent randomised controlled trial (RCT) demonstrated how VR training versus traditional methods allowed orthopaedic trainees to perform more correct steps, quicker, with more accurate component placement in cadaveric total hip arthroplasty [46]. Another RCT demonstrated how a curriculum of deliberate individualised practice in laparoscopic cholecystectomy on a VR simulator improved surgical performance of novices as rated by a blinded expert [45]. Advanced trainees can also benefit from VR simulator training. Following VR practice, trainees performed technically challenging advanced laparoscopic suturing on patients in theatre to a proficient level in less time and with fewer attempts than those trained conventionally [47]. The immersive nature of VR may encourage prolonged engagement with the training materials [45]. Unlike skills practice on cadavers, VR training can be repeated *ad ifinitum.*

AR technology can be used in a telementoring capacity to enhance trainee acquisition of skills. In one study, the trainer was able to provide real-time assistance through overlaid images of the surgical instruments onto the trainee's laparoscopic monitor. This resulted in an improved learning curve for achieving competence in laparoscopic suturing on a box trainer [48].

AR can be used to generate a live anatomical overlay, acting as surface landmark guidance for training in percutaneous procedures. Students demonstrated higher success rate in facet joint injection on a physical model with AR assistance [49]. Whether it is for teaching medical students on artificial anatomical models in the laboratory or on live patients in the operating theatre, AR anatomical guidance has fantastic educational potential.

3.2 Remote Teaching Ward Rounds

Remote MR ward rounds have been piloted as a modality for teaching medical students. However, data protection and information governance must be considered carefully when using technology to live stream patient interactions via an internet connection, especially if only for teaching purposes. A team from Imperial College London successfully overcame these complex governance issues to pilot hybrid, partially remote education ward rounds for medical students using HoloLens™ 2 during the COVID pandemic [50]. This was found to be an effective method of delivering ward-based teaching during the pandemic when students had limited patient exposure. The students found it particularly useful in that they could easily interact with the clinician leading the ward round and ask questions which they may not have done so easily if physically in front of the patient on a traditional ward round.

3.3 Acquisition of Clinical and Anatomical Knowledge

Highly realistic immersive VR experiences can facilitate learning and knowledge retention. Enhanced student engagement with anatomy learning materials using XR has been reported [51, 52]. A RCT study involving dental trainees demonstrated improved test scores following VR training on Le Fort osteotomy using Oculus Rift™ headsets compared to the control group taught via PowerPoint presentation [53]. They also reported improved self-confidence scores in performing the procedure. Huang et al. hypothesise that VR enhances knowledge retention by inducing feelings of "spatial presence" and through enjoyment of interacting with the virtual environment [54]. Moro et al. showed that skull anatomy teaching was equally effective when delivered using VR (via Oculus Rift™ headset), AR (via Samsung Galaxy™ S2 tablet) and conventional tablet-based resources, with no significant differences in test scores between the groups [55]. However, the students cited enhanced engagement and enjoyment whilst learning using VR and AR modalities versus regular screen-based material. A study of medical students showed greater time efficiency learning limb anatomy using HoloLens™—based anatomy software compared to cadaveric dissection. The MR anatomy group required less study time compared to the control group to achieve equivalent test scores [56].

VR can be used to enrich physical simulation by combining it with 3-D printed physical models. Highly customisable 3-D printed plastic anatomical models have been shown to be more effective in teaching complex anatomy to students compared to conventional ready-made plastic anatomical models and photographed anatomy atlases [57]. Barber et al. devised a virtual endoscopic sinus simulator using a 3D printed skull with patient-specific anatomy rendered from real patient CT imaging data. A virtual operating theatre environment was generated using the HTC VIVE™ VR HMD and a motion tracked 3D-printed mock endoscope could be inserted in the nasal cavity of the 3D printed skull. Endoscopic views of the nasal cavity were digitally recreated and shown on virtual screen within the VR operating theatre environment visualised through the HMD [58]. This high-fidelity multi-modality simulator with haptic feedback could be created at reasonably low cost.

3.4 Emergency Skills

VR can be utilised to practice low frequency, high pressure emergency scenarios without risk to patient safety [7]. Bongers et al. demonstrated how VR training can improve multitasking and problem-solving skills. Students were able to resolve laparoscopic insufflation problems more quickly following VR training compared to the control group [59]. VR training may be ideal for simulating rare events such as operating theatre fires, emergency airway management via front of neck access and major incident protocols. Trainees who received interactive Oculus Rift™ based VR training were able to manage an operating theatre fire more effectively compared to the control group who received didactic training [60].

3.5 VR Assessment of Surgical Performance

VR could prove to be a powerful tool in the assessment of trainee surgical performance. As trialled by Larsen et al., gynaecology trainees had to achieve a benchmark score on VR laparoscopic simulator before they were permitted to perform salpingectomy on live patients [61]. Other specialties are considering this approach for procedural benchmarking, for example in gastrointestinal endoscopy [62]. We predict that with the increased uptake and robust validation of such technologies, similar XR-based competence evaluations may be implemented in other surgical specialties. Ophthalmologists have demonstrated that performance on a VR cataract surgical simulator correlates to real-life surgical performance as assessed using a validated assessment score [63]. Another study used motion-tracking software to create a technical proficiency score for cataract surgery using average instrument movements and total path length. In addition to motion-tracked controllers or native tracking of the user's hands, several HMD manufacturers are implementing eye tracking within their hardware. We postulate that this technology, if interrogated carefully, can provide much needed insight into where a trainee looks for information during a scenario [64]. Trainee confidence in a procedure could be assessed with eye movement tracking, providing useful feedback as simulation becomes more complex and realistic. This suggests that VR simulators could be used not only as a training tool, but for assessment of technical proficiency also [65]. Wider utilisation of VR assessments of surgical competence may help to modernise UK surgical training, facilitating the shift away from a time-based training model towards a competency-based progression. It is perceivable that in the future, validated VR simulator assessments could assist the selection of surgeons for specialty training based on technical and visuo-spatial skills.

3.6 AI Autonomous Assessment of Surgical Performance

Machine learning algorithms have the potential to objectively evaluate surgeon performance [66, 67]. In urology, an algorithm has been developed to analyse intraoperative video footage from da Vinci surgical robots. It is able to evaluate procedure-specific surgical performance metrics such as camera and instrument movements, and with this predict clinical outcomes for the surgery [66]. By analysing surgical footage of robot-assisted radical prostatectomy, the algorithm was able to predict with 87% accuracy which patients would require a hospital stay of greater than two days [66]. Traditional evaluation of surgeon performance by peer observation is subject to bias and is extremely time consuming. In addition, small fluctuations in surgical performance may not be obviously perceptible to human trainers. There is potential for these machine learning algorithms to conduct autonomous, highly personalised performance assessments which would be greatly beneficial to surgical training. Automated video analysis would be time efficient and scalable, but more research is required to validate this before it is widely adopted for the training of robotic surgeons.

3.7 VR Surgical Training in the Developing World

It may seem like cutting-edge VR surgical training would be accessible only in resource-rich countries. Indeed, custom-built VR surgical simulators with haptic controls can cost up to £80,000 GBP [68].

The running costs of a traditional cadaveric dissection laboratory are considerable. Furthermore, each procedure or dissection can only be performed once on a cadaver before the integrity of the tissues are compromised. Conversely, technology-based simulation can be repeatedly re-used and can be regularly updated and improved over time. More recently, low-cost VR surgical simulation platforms have been developed using consumer computer gaming hardware. This may prove a cost-effective resource for training novice surgeons to reach proficiency in resource-challenged countries.

Bing et al. designed a VR training resource to teach Zambian gynaecology trainees to perform radical abdominal hysterectomy using Oculus Rift™ HMDs [69]. Their total hardware costs were approximately $1500 USD. It is estimated to cost $14,525 USD to train a surgeon in Zambia excluding trainee salary and costs of the mentor. The authors hypothesised that VR training could produce ‘pre-trained novices’, reducing surgical training time in Zambia and Malawi where there is a dearth of qualified surgeons with respect to population size.

3.8 VR Surgical Training Improves Patient Safety

Surgery has long been taught using a ‘master and apprentice model’. Trainees are guided through surgical procedures on real patients under the close observation of their trainer. Even under close supervision, an inexperienced surgeon wielding a scalpel carries a theoretical risk of harm to the patient [70]. Traditional surgical simulation on cadavers and artificial anatomical models allows trainees to practice without risk of harm to patients. Similarly, VR allows surgical trainees to practice surgical skills repetitively in a risk-free environment, improving technical proficiency and thus improving patient safety when it comes to performing the procedure on live patients [63]. But the true advantages of VR surgical simulation over cadaveric dissection is the repeatability, portability and comparatively low maintenance costs. In a RCT involving obstetric trainees, the group that trained on a laparoscopic VR simulator were able to perform salpingectomy on a live patient in half the time compared to the control group, potentially reducing morbidity risks of a prolonged procedure [61]. A Cochrane review similarly concluded that VR training reduced operating time in junior laparoscopic surgeons [44].

3.9 Limitations of TEL and XR Training Modalities

There are significant limitations to the use of XR technologies in surgical training. There have been great advances in the fidelity and detail of computer graphics and haptic feedback controllers—yet they cannot replace the feel and tactility of real human tissue. A fast and reliable internet connection is required for optimal running of multi-user XR surgical training programs—this is not consistently available even in UK NHS hospitals (although single-user programs can operate without an internet connection.) Many of the trials discussed in this paper have low participant numbers and are at high risk of selection, performance and detection bias [71]. In addition, motion sickness whilst using VR HMDs is a well reported side effect which can be intolerable for some [43].

3.9.1 Data Protection and Confidentiality

Patient confidentiality and data protection must be considered when using XR live-streaming and telementoring in a real clinical environment [72]. Different healthcare systems around the world have differing data protection requirements. It is imperative that all XR-based research, training and patient care adheres to these stipulations. We have begun to see institutions tackle this barrier. Imperial College London have established a HoloLens™ MR working group. They were able to overcome complex governance issues to successfully conduct remote ward rounds and live-streamed patient consultations for medical students [50]. Now the precedent has been set in the UK, we predict this to be approach will be translated nationally as the technology becomes more easily available and its benefits have been more widely demonstrated.

4 Conclusion

An unprecedented backlog of elective surgery has now accumulated due to COVID-19 disruptions. By reverting to 'business as usual', we will never succeed in clearing this. High volume, high turnover operating lists will be required; but the quality of surgical training will likely suffer as a result. It is vital that we embrace technological innovation to drive our healthcare systems towards recovery from the pandemic.

Timely yet carefully considered implementation of TEL, XR and AI technologies can:

1. **Enhance remote care** via virtual ward rounds and telementoring
2. **Enhance MDTs and pre-operative planning** through immersive experience
3. **Expedite clinical diagnosis** through automated photographic and radiological image recognition
4. **Expedite histological diagnosis** through automated specimen analysis
5. **Improve acquisition of clinical and anatomical knowledge** through engaging, interactive virtual platforms
6. **Enhance acquisition of surgical and emergency skills** and encourage practice in a risk-free environment
7. **Reduce the cost of surgical training** versus traditional cadaveric dissection
8. **Improve objectivity, consistency and accuracy in assessment of a trainee's surgical competence**
9. **Recuperate training experience lost** during the COVID-19 pandemic
10. And ultimately **improve patient safety** and minimise harm though high-quality training and greater efficiency in the delivery of surgical care

References

1. COVIDSurg Collaborative: Elective surgery cancellations due to the COVID-19 pandemic: global predictive modelling to inform surgical recovery plans. Br. J. Surg. **107**(11), 1440–1449 (2020). https://doi.org/10.1002/bjs.11746
2. The Guardian: Number of people on England's NHS waiting list tops 5m for first time. 2021 Accessed https://www.theguardian.com/society/2021/jun/10/number-of-people-on-englands-nhs-waiting-list-tops-5m-for-first-time
3. The Health Foundation: Elective care in England. Assessing the impact of COVID-19 and where next (2020). Accessed https://www.health.org.uk/publications/long-reads/elective-care-in-england-assessing-the-impact-of-covid-19-and-where-next
4. Sud, A., Jones, M.E., Broggio, J., Loveday, C., Torr, B., Garrett, A., et al.: Collateral damage: the impact on outcomes from cancer surgery of the COVID-19 pandemic. Ann. Oncol. **31**(8), 1065–1074 (2020). https://doi.org/10.1016/j.annonc.2020.05.009
5. Tiffany, K.: It's cool to look terrifying on pandemic instagram. The Atlantic (2020). https://wwwtheatlanticcom/technology/archive/2020/05/augmented-reality-instagram-zoom/611494/
6. Bourne, J.: 'Bright future' for AR and VR in 2021 and beyond, says strategy analytics. VR360 (2020). https://virtualreality-newsnet/news/2020/jul/14/bright-future-for.-.ar-and-vr-in-2021-and-beyond-says-strategy-analytics/
7. Abbas, J.R., Kenth, J.J., Bruce, I.A.: The role of virtual reality in the changing landscape of surgical training. J. Laryngol Otol. 1–4 (2020). https://doi.org/10.1017/s0022215120002078
8. Topol, E.: Preparing the healthcare workforce to deliver the digital future. The Topol Review: An Independent Report on Behalf of the Secretary of State for Health and Social Care February 2019 (2019). https://topol.hee.nhs.uk/wp-content/uploads/HEE-Topol-Review-2019.pdf
9. Insight: Alder Hey Children's Hospital Pioneers Remote Clinical Care with Microsoft HoloLens 2 and Dynamics 365 Remote Assist. Accessed https://www.uk.insight.com/en-gb/content-and-resources/2020/case-studies/alder-hey-childrens-hospital-pioneers-remote-clinical-care.
10. Levy, J.B., Kong, E., Johnson, N., Khetarpal, A., Tomlinson, J., Martin, G.F., et al.: The mixed reality medical ward round with the MS HoloLens 2: innovation in reducing COVID-19 transmission and PPE usage. Future Healthc J. **8**(1), e127–e130 (2021). https://doi.org/10.7861/fhj.2020-0146
11. Martin, G., Koizia, L., Kooner, A., Cafferkey, J., Ross, C., Purkayastha, S., et al.: Use of the HoloLens2 mixed reality headset for protecting health care workers during the COVID-19 pandemic: prospective, observational evaluation. J. Med. Internet. Res. **22**(8), e21486 (2020). https://doi.org/10.2196/21486
12. Kumar, R.P., Pelanis, E., Bugge, R., Brun, H., Palomar, R., Aghayan, D.L., et al.: Use of mixed reality for surgery planning: assessment and development workflow. J. Biomed. Inform.: X. **8**, 100077 (2020)
13. Oeppen, R.S., Davidson, M., Scrimgeour, D.S., Rahimi, S., Brennan, P.A.: Human factors awareness and recognition during multidisciplinary team meetings. J. Oral Pathol. Med. **48**(8), 656–661 (2019). https://doi.org/10.1111/jop.12853
14. FDA News: FDA clears microsoft's HoloLens for pre-operative surgical planning. Accessed https://www.fdanews.com/articles/188966-fda-clears-microsofts-hololens-for-pre-operative-surgical-planning
15. Gibby, J.T., Swenson, S.A., Cvetko, S., Rao, R., Javan, R.: Head-mounted display augmented reality to guide pedicle screw placement utilizing computed tomography. Int. J. Comput. Assist. Radiol. Surg. **14**(3), 525–535 (2019). https://doi.org/10.1007/s11548-018-1814-7
16. Dennler, C., Jaberg, L., Spirig, J., Agten, C., Götschi, T., Fürnstahl, P., et al.: Augmented reality-based navigation increases precision of pedicle screw insertion. J. Orthop. Surg. Res. **15**(1), 174 (2020). https://doi.org/10.1186/s13018-020-01690-x

17. Pratt, P., Ives, M., Lawton, G., Simmons, J., Radev, N., Spyropoulou, L., et al.: Through the HoloLens™ looking glass: augmented reality for extremity reconstruction surgery using 3D vascular models with perforating vessels. Eur. Radiol. Exp. **2**(1), 2 (2018). https://doi.org/10.1186/s41747-017-0033-2
18. Al Janabi, H.F., Aydin, A., Palaneer, S., Macchione, N., Al-Jabir, A., Khan, M.S., et al.: Effectiveness of the HoloLens mixed-reality headset in minimally invasive surgery: a simulation-based feasibility study. Surg. Endosc. **34**(3), 1143–1149 (2020). https://doi.org/10.1007/s00464-019-06862-3
19. Rojas-Muñoz, E., Cabrera, M.E., Lin, C., Andersen, D., Popescu, V., Anderson, K., et al.: The System for Telementoring with Augmented Reality (STAR): A head-mounted display to improve surgical coaching and confidence in remote areas. Surgery **167**(4), 724–731 (2020). https://doi.org/10.1016/j.surg.2019.11.008
20. Goodfellow, I., Bengio, Y., Courville, A.: Deep Learning. MIT press, Cambridge (2016)
21. Kok, J.N., Boers, E.J., Kosters, W.A., Van der Putten, P., Poel, M.: Artificial intelligence: definition, trends, techniques, and cases. Artif. Intell. **1**, 270–299 (2009)
22. Artificial Intelligence In Healthcare Market Size, Share & Trends Analysis Report By Component (Hardware, Software, Services), By Application, By Region, Competitive Insights, And Segment Forecasts, 2019–2025. Accessed https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-healthcare-market
23. FDA-approved AI-based algorithms. Accessed https://medicalfuturist.com/fda-approved-ai-based-algorithms/
24. Benjamens, S., Dhunnoo, P., Meskó, B.: The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database. NPJ. Digit. Med. **3**, 118 (2020). https://doi.org/10.1038/s41746-020-00324-0
25. Topol, E.J.: High-performance medicine: the convergence of human and artificial intelligence. Nat. Med. **25**(1), 44–56 (2019). https://doi.org/10.1038/s41591-018-0300-7
26. Choy, G., Khalilzadeh, O., Michalski, M., Do, S., Samir, A.E., Pianykh, O.S., et al.: Current applications and future impact of machine learning in radiology. Radiology **288**(2), 318–328 (2018). https://doi.org/10.1148/radiol.2018171820
27. Crowson, M.G., Ranisau, J., Eskander, A., Babier, A., Xu, B., Kahmke, R.R., et al.: A contemporary review of machine learning in otolaryngology-head and neck surgery. Laryngoscope. **130**(1), 45–51 (2020). https://doi.org/10.1002/lary.27850
28. Heydon, P., Egan, C., Bolter, L., Chambers, R., Anderson, J., Aldington, S., et al.: Prospective evaluation of an artificial intelligence-enabled algorithm for automated diabetic retinopathy screening of 30 000 patients. Br. J. Ophthalmol. (2020). https://doi.org/10.1136/bjophthalmol-2020-316594
29. Abràmoff, M.D., Lavin, P.T., Birch, M., Shah, N., Folk, J.C.: Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. NPJ. Digit. Med. **1**, 39 (2018). https://doi.org/10.1038/s41746-018-0040-6
30. Ozkaya, E., Topal, F.E., Bulut, T., Gursoy, M., Ozuysal, M., Karakaya, Z.: Evaluation of an artificial intelligence system for diagnosing scaphoid fracture on direct radiography. Eur. J. Trauma Emerg. Surg. (2020). https://doi.org/10.1007/s00068-020-01468-0
31. FDA: Evaluation of Automatic Class III Designation for OsteoDetect. Accessed https://www.accessdata.fda.gov/cdrh_docs/reviews/DEN180005.pdf
32. Liu, G.S., Zhu, M.H., Kim, J., Raphael, P., Applegate, B.E., Oghalai, J.S.: ELHnet: a convolutional neural network for classifying cochlear endolymphatic hydrops imaged with optical coherence tomography. Biomed. Opt. Express. **8**(10), 4579–4594 (2017). https://doi.org/10.1364/boe.8.004579
33. Chowdhury, N.I., Smith, T.L., Chandra, R.K., Turner, J.H.: Automated classification of osteomeatal complex inflammation on computed tomography using convolutional neural networks. Int. Forum Allergy Rhinol. **9**(1), 46–52 (2019). https://doi.org/10.1002/alr.22196
34. Clinical trial shows breast screening AI could assist radiologists in detecting cancer in mammograms. Accessed https://www.mobihealthnews.com/news/emea/clinical-trial-shows-breast-screening-ai-could-assist-radiologists-detecting-cancer

35. Breast screening and coronavirus: up to 1 million women miss their mammogram. Accessed https://breastcancernow.org/about-us/news-personal-stories/breast-screening-coronavirus-1-million-women-miss-their-mammogram
36. Halicek, M., Dormer, J.D., Little, J.V., Chen, A.Y., Myers, L., Sumer, B.D., et al.: Hyperspectral imaging of head and neck squamous cell carcinoma for cancer margin detection in surgical specimens from 102 patients using deep learning. Cancers (Basel) **11**(9) (2019). https://doi.org/10.3390/cancers11091367
37. Steiner, D.F., MacDonald, R., Liu, Y., Truszkowski, P., Hipp, J.D., Gammage, C., et al.: Impact of deep learning assistance on the histopathologic review of lymph nodes for metastatic breast cancer. Am. J. Surg. Pathol. **42**(12), 1636–1646 (2018). https://doi.org/10.1097/pas.0000000000001151
38. Ström, P., Kartasalo, K., Olsson, H., Solorzano, L., Delahunt, B., Berney, D.M., et al.: Artificial intelligence for diagnosis and grading of prostate cancer in biopsies: a population-based, diagnostic study. Lancet Oncol. **21**(2), 222–232 (2020). https://doi.org/10.1016/s1470-2045(19)30738-7
39. The Artificial Intelligence in Health and Care Award. Accessed https://www.nhsx.nhs.uk/ai-lab/ai-lab-programmes/ai-health-and-care-award/.
40. Cruz Rivera, S., Liu, X., Chan, A.W., Denniston, A.K., Calvert, M.J.: Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension. Nat Med. **26**(9), 1351–1363 (2020). https://doi.org/10.1038/s41591-020-1037-7
41. Zawati, M., Lang, M.: What's in the box?: uncertain accountability of machine learning applications in healthcare. Am. J. Bioeth. **20**(11), 37–40 (2020). https://doi.org/10.1080/15265161.2020.1820105
42. RCSEng: Improving surgical training. The Royal College of Surgeons of England (2015)
43. Munafo, J., Diedrick, M., Stoffregen, T.A.: The virtual reality head-mounted display Oculus Rift induces motion sickness and is sexist in its effects. Exp. Brain Res. **235**(3), 889–901 (2017). https://doi.org/10.1007/s00221-016-4846-7
44. Nagendran, M., Gurusamy, K.S., Aggarwal, R., Loizidou, M., Davidson, B.R.: Virtual reality training for surgical trainees in laparoscopic surgery. Cochrane Database Syst. Rev. **2013**(8), Cd006575 (2013). https://doi.org/10.1002/14651858.CD006575.pub3
45. Palter, V.N., Grantcharov, T.P.: Individualized deliberate practice on a virtual reality simulator improves technical performance of surgical novices in the operating room: a randomized controlled trial. Ann. Surg. **259**(3), 443–448 (2014). https://doi.org/10.1097/sla.0000000000000254
46. Logishetty, K., Rudran, B., Cobb, J.P.: Virtual reality training improves trainee performance in total hip arthroplasty: a randomized controlled trial. Bone Joint J. **101-b**(12), 1585–1592 (2019). https://doi.org/10.1302/0301-620x.101b12.Bjj-2019-0643.R1
47. Orzech, N., Palter, V.N., Reznick, R.K., Aggarwal, R., Grantcharov, T.P.: A comparison of 2 ex vivo training curricula for advanced laparoscopic skills: a randomized controlled trial. Ann. Surg. **255**(5), 833–839 (2012). https://doi.org/10.1097/SLA.0b013e31824aca09
48. Vera, A.M., Russo, M., Mohsin, A., Tsuda, S.: Augmented reality telementoring (ART) platform: a randomized controlled trial to assess the efficacy of a new surgical education technology. Surg. Endosc. **28**(12), 3467–3472 (2014). https://doi.org/10.1007/s00464-014-3625-4
49. Yeo, C.T., Ungi, T., Paweena, U., Lasso, A., McGraw, R.C., Fichtinger, G.: The effect of augmented reality training on percutaneous needle placement in spinal facet joint injections. IEEE Trans. Biomed. Eng. **58**(7), 2031–2037 (2011). https://doi.org/10.1109/tbme.2011.2132131
50. Bala, L., Kinross, J., Martin, G., Koizia, L.J., Kooner, A.S., Shimshon, G.J., et al.: A remote access mixed reality teaching ward round. Clin. Teach. (2021). https://doi.org/10.1111/tct.13338
51. Ekstrand, C., Jamal, A., Nguyen, R., Kudryk, A., Mann, J., Mendez, I.: Immersive and interactive virtual reality to improve learning and retention of neuroanatomy in medical students: a randomized controlled study. CMAJ Open **6**(1), E103–E109 (2018). https://doi.org/10.9778/cmajo.20170110

52. Stepan, K., Zeiger, J., Hanchuk, S., Del Signore, A., Shrivastava, R., Govindaraj, S., et al.: Immersive virtual reality as a teaching tool for neuroanatomy. Int. Forum Allergy Rhinol. **7**(10), 1006–1013 (2017). https://doi.org/10.1002/alr.21986
53. Pulijala, Y., Ma, M., Pears, M., Peebles, D., Ayoub, A.: Effectiveness of immersive virtual reality in surgical training-a randomized control trial. J. Oral Maxillofac. Surg. **76**(5), 1065–1072 (2018). https://doi.org/10.1016/j.joms.2017.10.002
54. Huang, K.T., Ball, C., Francis, J., Ratan, R., Boumis, J., Fordham, J.: Augmented versus virtual reality in education: an exploratory study examining science knowledge retention when using augmented reality/virtual reality mobile applications. Cyberpsychol Behav. Soc. Netw. **22**(2), 105–110 (2019). https://doi.org/10.1089/cyber.2018.0150
55. Moro, C., Štromberga, Z., Raikos, A., Stirling, A.: The effectiveness of virtual and augmented reality in health sciences and medical anatomy. Anat. Sci. Educ. **10**(6), 549–559 (2017). https://doi.org/10.1002/ase.1696
56. Ruthberg, J.S., Tingle, G., Tan, L., Ulrey, L., Simonson-Shick, S., Enterline, R., et al.: Mixed reality as a time-efficient alternative to cadaveric dissection. Med. Teach. **42**(8), 896–901 (2020). https://doi.org/10.1080/0142159x.2020.1762032
57. Ye, Z., Dun, A., Jiang, H., Nie, C., Zhao, S., Wang, T., et al.: The role of 3D printed models in the teaching of human anatomy: a systematic review and meta-analysis. BMC Med. Educ. **20**(1), 335 (2020). https://doi.org/10.1186/s12909-020-02242-x
58. Barber, S.R., Jain, S., Son, Y.J., Chang, E.H.: Virtual functional endoscopic sinus surgery simulation with 3d-printed models for mixed-reality nasal endoscopy. Otolaryngol. Head Neck Surg. **159**(5), 933–937 (2018). https://doi.org/10.1177/0194599818797586
59. Bongers,. P.J., Diederick van Hove, P., Stassen, L.P.S., Dankelman, J., Schreuder, H.W.R.: A new virtual-reality training module for laparoscopic surgical skills and equipment handling: can multitasking be trained? A randomized controlled trial. J. Surg. Educ. **72**(2):184–191 (2015). https://doi.org/10.1016/j.jsurg.2014.09.004
60. Sankaranarayanan, G., Wooley, L., Hogg, D., Dorozhkin, D., Olasky, J., Chauhan, S., et al.: Immersive virtual reality-based training improves response in a simulated operating room fire scenario. Surg. Endosc. **32**(8), 3439–3449 (2018). https://doi.org/10.1007/s00464-018-6063-x
61. Larsen, C.R., Soerensen, J.L., Grantcharov, T.P., Dalsgaard, T., Schouenborg, L., Ottosen, C., et al.: Effect of virtual reality training on laparoscopic surgery: randomised controlled trial. BMJ **338**, b1802 (2009). https://doi.org/10.1136/bmj.b1802
62. Ekkelenkamp, V.E., Koch, A.D., de Man, R.A., Kuipers, E.J.: Training and competence assessment in GI endoscopy: a systematic review. Gut **65**(4), 607–615 (2016). https://doi.org/10.1136/gutjnl-2014-307173
63. Jacobsen, M.F., Konge, L., Bach-Holm, D., la Cour, M., Holm, L., Højgaard-Olsen, K., et al.: Correlation of virtual reality performance with real-life cataract surgery performance. J. Cataract. Refract. Surg. **45**(9), 1246–1251 (2019). https://doi.org/10.1016/j.jcrs.2019.04.007
64. Wagner, M., Gröpel, P., Bibl, K., Olischar, M., Auerbach, M.A., Gross, I.T.: Eye-tracking during simulation-based neonatal airway management. Pediatr. Res. **87**(3), 518–522 (2020). https://doi.org/10.1038/s41390-019-0571-9
65. Thomsen, A.S., Smith, P., Subhi, Y., Cour, M., Tang, L., Saleh, G.M., et al.: High correlation between performance on a virtual-reality simulator and real-life cataract surgery. Acta Ophthalmol. **95**(3), 307–311 (2017). https://doi.org/10.1111/aos.13275
66. Hung, A.J., Chen, J., Gill, I.S.: Automated performance metrics and machine learning algorithms to measure surgeon performance and anticipate clinical outcomes in robotic surgery. JAMA Surg. **153**(8), 770–771 (2018). https://doi.org/10.1001/jamasurg.2018.1512
67. Khalid, S., Goldenberg, M., Grantcharov, T., Taati, B., Rudzicz, F.: Evaluation of deep learning models for identifying surgical actions and measuring performance. JAMA Netw. Open. **3**(3), e201664 (2020). https://doi.org/10.1001/jamanetworkopen.2020.1664
68. Wade, A.: UK firm claims haptic VR surgery simulation can cost less than cadaver. https://www.theengineer.co.uk/haptic-vr-surgery-simulation/#:~:text=According%20to%20FundameltalVR%2C%20a%20single,surgeons%20enjoy%20access%20to%20them.2018

69. Bing, E.G., Parham, G.P., Cuevas, A., Fisher, B., Skinner, J., Mwanahamuntu, M., et al.: Using low-cost virtual reality simulation to build surgical capacity for cervical cancer treatment. J. Glob. Oncol. **5**, 1–7 (2019). https://doi.org/10.1200/jgo.18.00263
70. Akhtar, K.S., Chen, A., Standfield, N.J., Gupte, C.M.: The role of simulation in developing surgical skills. Curr. Rev. Musculoskelet Med. **7**(2), 155–160 (2014). https://doi.org/10.1007/s12178-014-9209-z
71. Piromchai, P., Avery, A., Laopaiboon, M., Kennedy, G., O'Leary, S.: Virtual reality training for improving the skills needed for performing surgery of the ear, nose or throat. Cochrane Database Syst. Rev. **2015**(9), Cd010198. https://doi.org/10.1002/14651858.CD010198.pub2
72. Khor, W.S., Baker, B., Amin, K., Chan, A., Patel, K., Wong, J.: Augmented and virtual reality in surgery-the digital surgical environment: applications, limitations and legal pitfalls. Ann. Transl. Med. **4**(23), 454 (2016). https://doi.org/10.21037/atm.2016.12.23

A Biomarker-Based Model to Assist the Identification of Stress in Health Workers Involved in Coping with COVID-19

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Abstract Health professionals are constantly exposed to stressful situations in their places of work. When stress becomes something negative in the work routine, creating challenges for the correct performance of their practices, failure can be one of the consequences. The COVID-19 pandemic clearly showed how much the frontline health professional needs support in situations of extreme demand. This chapter presents a theoretical study focused on the health of these professionals who work on the front lines, presenting a model based on biomarkers for identifying and classifying stress levels. This model is going to be integrate in a recommender system aiming to proactively propose mitigation actions in the surveillance of occupational stress of these professionals. Furthermore, exploration and analysis of biomarkers that can

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assist in monitoring the professional were carried out so that excessive and constant stress does not result in the need for their removal, thus further impairing patient care services.

Keywords Occupational stress · Biomarkers · Internet of things · Recommender systems

1 Introduction

Due to the Sars-Cov-2 virus pandemic, healthcare professionals have faced an intense stress load, with long working hours, overload of tasks, lack of protective equipment, and permanent need for concentration. In addition, they receive diverse instructions, strict security measures, and surveillance, including reduced social contact in the whole world [1, 2]. All over the world, since the beginning of the pandemic, there are reports of contamination and death of these health professionals and suicide records, reinforcing the information that the psychological effect of the disease is devastating [3]. In the study carried out between 2003 and 2016 by Ji et al. [4], the authors present risk factors that can lead these professionals to commit suicide. The results of the data analysis helped to detect the worsening of occupational stress (burnout) and the use of this information for interventions to prevent the act of taking one's own life. It is noteworthy that the nursing activity points to a psychic overload concerning other health professionals arising from the chronic stress of daily life [5]. Excessive doses can lead to undesirable consequences such as extreme fatigue, insomnia, irritability, anxiety, depression, and lack of concentration, negatively interfering in the work environment and, consequently, decreasing the individuals' productivity [1, 6]. Therefore, the stressful conditions that health teams have been experiencing around the world can lead to failures, not only in the correct use of personal protective equipment (PPE), but also in the care of infected patients, putting the patient's health at risk, the professional and his team, and even his family [1, 3]. In other words, it is essential to prioritize actions so that these conditions can be identified early and, with this, attenuate the adverse outcomes [1, 7, 8]. The damages caused range from lost productivity, work accidents, increased health costs, and absenteeism at work [2, 9]. According to David Koh [10], the physical signs of stress can be observed in the form of excessive sweating, stomach pain, dry mouth, cold extremities, cardiac acceleration, wheezing, tremors, hypertension; or else it manifests itself in mind through insecurity, insomnia, anguish, hopelessness, fears, panic, etc.

Based on the above, this chapter aims to present a study on biomarkers that aim to help identify occupational stress and, associating deep machine learning techniques, to model a system to assist in occupational stress surveillance. When dealing with different types of context and volume of information, deep learning has been recommended in problems with a high degree of complexity [11–13]. Through the study of these approaches, ways of extracting data with stress characteristics are proposed. and recommending actions to face it [12, 14]. We also highlight the investigation of techniques that may be explainable, associated with the development of the system. Thus, the study presented here intends to seek the possibilities of identifying physiological factors represented by biomarkers to help mitigate these symptoms with health professionals. With this, avoid chronic stress in the face of the current moment of coping with the pandemic.

The chapter is organized into five sections. Section 2 presents issues related to the stress of health workers. Section 3 presents a theoretical study of biomarkers that can be applied to a wearable device. Section 4 proposes a discussion on modeling a system for the Internet of Things (IoT), biomarkers, and machine learning to identify stress symptoms. The summary, final considerations, and bibliographical references follow.

2 Health Workers and Occupational Stress

According to Ruotsalainen et al. [15], health professionals, especially those who work on the front lines in situations of high emotional overload, are highly likely to suffer from occupational stress because of the lack of skills, organizational factors, and low social support at work, leading to anguish, exhaustion, and psychosomatic problems, in addition to the deterioration of quality of life and service provision. Many of these professionals can cope well with adaptations and stressful moments but tolerating long periods in these conditions without any illness (physical or psychological) is more complex, which can cause consistent loss of health, absence from work, and a condition of chronic stress. Moreover, in the specific crisis of the COVID-19 pandemic, the exposure to various situations of suffering and impotence in the face of varied pain conditions, the possibility of death in people of different ages, and multiple conditions added to the possibility of illness of the professional. The occupational stress among these professionals is considered to result from submission to the job stressors or environmental stressors at work, accomplishment there are different stress factors in the workplace of health professionals, such as high hours' journey, overloaded, work pressure, effects at the personal life, weak social support, and lack of participation at the decision-making process. This increases the risk of distress and burnout consequently. Furthermore, there is a high economic impact resulting from absenteeism and turnover of the health workers [16]. It is worth considering that work-related stress does not simply disappear when the worker goes home for the day. When stress persists, it can affect health and well-being more generally. In the case of workers who work on the front lines of COVID-19, an increase in work intensity and, consequently, an increase in fatigue due to work overload has been reported. The number of infected professionals demands longer shifts in the workday. In addition, the adaptation with personal protective equipment requires rigorous care to perform simple tasks, such as drinking water, breathing, and the vision itself, which is compromised. This demands more effort, concentration, and, consequently, more significant emotional wear, leading in some cases to exhaustion from work [7, 8].

Several works present different methodologies based on the application of questionnaires and self-report scales to assess occupational stress, pointing out cases of Burnout Syndrome and other consequences due to occupational stress, specifically in the health area [17–22]. There are different approaches for a formal definition for burnout, for example, "burnout is a syndrome of emotional exhaustion, depersonalization, and reduce personal accomplishment that can occur among individuals, what do people work of some kind [19]" or "burnout is a persistent, negative, work-related state of mind in normal individuals that is primarily characterized by exhaustion, which is accompanied by distress, sense of reduced effectiveness, decrease motivation, and the development of dysfunctional attitudes and behaviors at work [15]". Important to highlight that burnout symptoms occur in "healthy" individuals, it means, individuals who do not suffer from mental disease or psychopathologies. In the health workers [20] several work conditions have been identified as stressors, such as long hours worked, overloaded, some pressure about the team, lack of control about the job journey, social life effects, lack of participation in the decision-making process, and weak social support. Because of the severe suffering, exhaustion, emotional, and physical illness, also were pointed to a reduced life quality and high costs as absenteeism and turnover in the job. The authors related that these psychological illnesses may be potentially changed by some interventions as shown by some investigations.

Another difficulty in identifying and evaluating automatically is since the changes in the body are the same for both positive and negative situations. To integrate several contributions, Fig. 1 synthesizes signs that arise with the presence of positive and negative stress, according to some articles read in this area [23, 24]. Emphasizing that occupational stress is from resulting in-state experience from a sense of reduced effectiveness, a decrease of motivation, and other bad experiences from the job occupation [20].

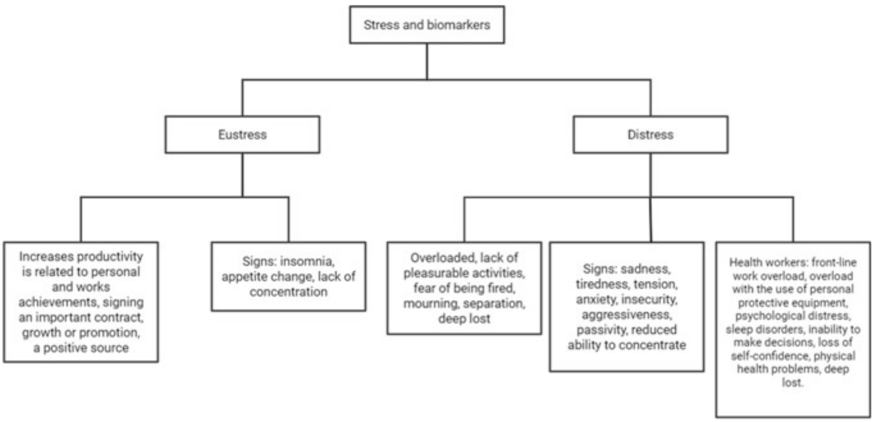

Fig. 1 Signals to identify the positive and negative stress

In addition, signs pointed out by health professionals on the front line in different studies carried out on this topic by other researchers were added to negative stress. These data reflect signs found at the current time of the pandemic and during the crisis facing SARS published in 2004 [1, 2, 7, 8]. When the body is in eustress, it is associated with favorable situations, leading to extreme happiness, and generating symptoms such as insomnia, change in appetite, and lack of concentration, generating increased productivity in terms of work activities. On the contrary, distress has only negative consequences, such as sadness, fatigue, tension, anxiety, insecurity, reduced ability to concentrate, aggressiveness, or even passivity. Distress can be associated with overwork, fear of being fired, lack of pleasurable activities, and working environment conditions. For example, in a study of nurses working on the front line of the Covid-19 pandemic, about 73.8% had symptoms of stress, and 25% were identified with psychological distress [1]. This is because they are working in the hospital, fearing contracting the disease or transmitting it to family members. It is also noteworthy that occupational stress can present three distinct stages: acute, episodic, and chronic [23, 25]. Acute stress is that of the body's immediate response and presents an increase in heart rate, change in respiratory rate, energy mobilization, loss of appetite, change in glucose, fluid retention, increased blood flow, muscle changes, and possible responses of each organism. While chronic stress is one in which signs may persist for days, weeks, or even months [26].

3 Biomarkers

Health professionals, more specifically those acting on the front lines of combating Covid-19, have been undergoing an extremely stressful routine since last year due to the pandemic. Among the most frequent complaints reported are the lack of resources in hospitals and health facilities (PPE, respirators, medication, etc.), fear of contaminating family members, fear of contracting the disease, and working hours with few employees due to the high rate of infections that have been recorded since the beginning in March 2020 [3]. Amidst this chaos, it is challenging to monitor the situation of these professionals through the consolidated methods of stress identification. According to a theoretical study on psychosocial changes related to workers, it is possible to create personal coping strategies early [24]. Faced with stressors, the human organism prepares for the extreme, or flight, or fight. It is possible to perceive it through the physiological changes of each individual. Among the reactions are sweating, rapid heartbeat, and hormonal changes. This physical alertness can also result in changes in the skin's constricting vessels to reduce bleeding, and the increased heart rate also helps to increase oxygen flow [5, 23, 27]. In addition, some hormones can help to identify stress more accurately, such as cortisol and others shown in [26].

3.1 Biomarkers for Stress Identification

Articles in the scientific literature point to the use of biomarkers to identify stress in different types of situations: driving, performing cognitive activities or even different work activities. Analyzing some of these works, the biomarkers with the highest degree of confidence for stress classification are cardiac and brain activities and skin conductivity. Other biomarkers that also stand out in this context are blood pressure, skin temperature, and respiration [27, 28]. Three metrics have been identified as the most reliable and non-invasive. These physiological measures are related to the autonomic nervous system, composed of two subsystems: the sympathetic nervous system and the parasympathetic nervous system. These two systems regulate the body's response, producing physiological variations identified through changes in biomarkers [24]. Of the countless biomarkers mentioned in the literature, those used to compose a wearable wrist device to identify occupational stress are investigated. It seeks to establish the values of changes in the physiological conditions of individuals that were mentioned in previous works [13, 23, 29]. These indices will be discussed in the next section.

3.2 Parameters for Measurement

There are measurements of invasive parameters and other types of measurement considered non-invasive, and several biomarkers have been researched to address the identification of stress in individuals [30]. Invasive methods are related to biochemical factors that mainly show hormonal changes related to physiological and behavioral changes in the face of stressors [26]. However, non-invasive forms are promising for identifying stress. Some of these parameters have been investigated over time, showing a degree of reliability for identifying acute or chronic stress in their research. In some cases, the parameters are associated with improving the credibility of the results [23, 29, 31]. Next, the parameters that can be applied to a wristwear will be highlighted and are related to cardiac activities, skin conductance, and body temperature. Other parameters can also be used for stress assessment and have been registered in recent years, but they will not be the object of this theoretical study. Some biomarkers show changes, both physical and physiological, due to the sympathetic nervous system that increases the level of hormones, changing homeostasis and causing changes in the body, such as changes in the musculature, pupil diameter, blood pressure, glucose level, cortisol, and breathing [23, 32, 33].

3.2.1 Cardiac Activities

Many authors consider heart rate variations to be an efficient non-invasive measure to detect cardiovascular conditions. These variations are directly related to the activities of the autonomic nervous system (ANS) and are therefore considered a reliable parameter to monitor stress [34, 35]. Furthermore, heart rate variation reflects the ability of individuals to adapt to changes. Heart rate variability can be measured by optical sensors or by ECG (Electrocardiogram). The ECG provides a graphic record of the electrical activity produced by the cardiac muscle, and it is possible to use it in wireless wearable devices as shown in [29]. However, as it requires electrodes, it does not apply to the development of a wearable device. In recent years, in some devices used for cardiac monitoring during physical activities, measurement by optical sensors has been used, which work through light beams that cross the skin layers and measure blood volume changes in the pulse area. These devices also have other types of sensors that can be associated with them and that measure through a strap used at chest height. Heart variability can be analyzed in the time domain or its frequency domain [33]. In a review of stress biomarkers, baseline heart rate depends on the individual's cardiovascular fitness, which is individual measurements. According to the survey, the most prominent measure for calculating cardiac variation is the mean of the RR interval. A low value of this measure indicates the stress condition. Among the parameters considered in the articles, mean, median, variance, and heart rate stand out [28, 34, 36]. While in the frequency domain, stress conditions are more prominent in high-frequency and low-frequency data analysis. A low frequency is associated with the sympathetic nervous system and is around 0–0.08 Hz, or 0.04–0.15 Hz. In contrast, the high frequency is associated with the parasympathetic nervous system and is around 0.15–0.5 Hz or 0.16–0.4 Hz or even 0.05–0.15 Hz. These variations are related to changes in respiratory rate. In intense physical activity or deep relaxation, these ranges of values should be changed [23].

3.2.2 Skin Conductance and Skin Temperature

Changes in the individual's skin are measured using the GSR (Galvanic Skin Response). Skin conductance increases when the individual is in a stressful situation. Because it elevates the moisture on the skin's surface and consequently increases the individual's flow of electricity. When the individual is less stressed, the conductance decreases, there are some devices on the market to measure the skin conductance of individuals and are presented in [18]. One way to increase the measurement credibility using the GSR is associating it with other parameters, such as the Blood Volume Pulse (BVP) measurement, which reduces when the individual is in a stressful situation [20]. Few references were found regarding the subjects' body temperature and stress. However, it is also considered a parameter that can be easily associated with a wearable wrist device, and its information can improve the confidence of the result of stress identification and assessment [27, 37, 38].

4 Biomarker-Based Model Recommender System

Both eustress and distress can generate changes in the body's homeostasis due to changes in physiological, physical, and chemical signs in the body of individuals due to the presence of stressors, as mentioned above [23]. Through the theoretical discussion about biomarkers, it is possible to design a wearable device to acquire individual data. In addition, the study investigates ways to compose a model that transmits these data to an intermediate unit in an Internet of Things infrastructure so that this information can help manage people who work on the front lines of the pandemic. Combining artificial intelligence resources and applying other computational techniques, the system should provide recommendations to alleviate symptoms of occupational stress early and serve as support for the management of people within a hospital unit.

4.1 Internet of Things

The Internet of Things is an ecosystem composed of various technological devices with the ability to perform numerous functions, such as supporting the monitoring of stress conditions pointed out in this chapter. There are different types of sensors, communication protocols, platforms for data acquisition, information processing, distribution, security, and synchronism. These features allow the development of a multimodal data capture system with feature extraction, pre-processing in an intermediate system, classification, and later distribution and synchronism, presenting recommendations to mitigate the stress situation, or recommending the search for professional help according to the classification indicated by the system. An infrastructure for IoT healthcare can be developed with 3 or 4 layers, as presented in [39].

Figure 2 presents a layered architecture proposed by the authors for the system considering a device for IoT healthcare. This type of problem requires a layered architecture to meet the specifics and functionalities of a possible solution. For example, the volume of information collected, transmitted, and processed needs to be forwarded to an intermediate level (such as a fog layer or edge computing) not to overload the network and increase the delay in transmitting and processing information. Data collection is carried out by sensors, which may comprise a wearable device (imagine a wrist wearable to facilitate day-to-day use). After acquiring this data, they are sent via a wireless protocol (in this case, it could be 6LowPAN, or even WiFi or Bluetooth itself, given the distance and amount of data that needs to be forwarded and the frequency of updating the information). These characteristics will be deepened at another time, with the specific study for developing the acquisition hardware. The pre-processing layer performs the analysis and classification of information and is subsequently transmitted to the cloud computing, and from this system

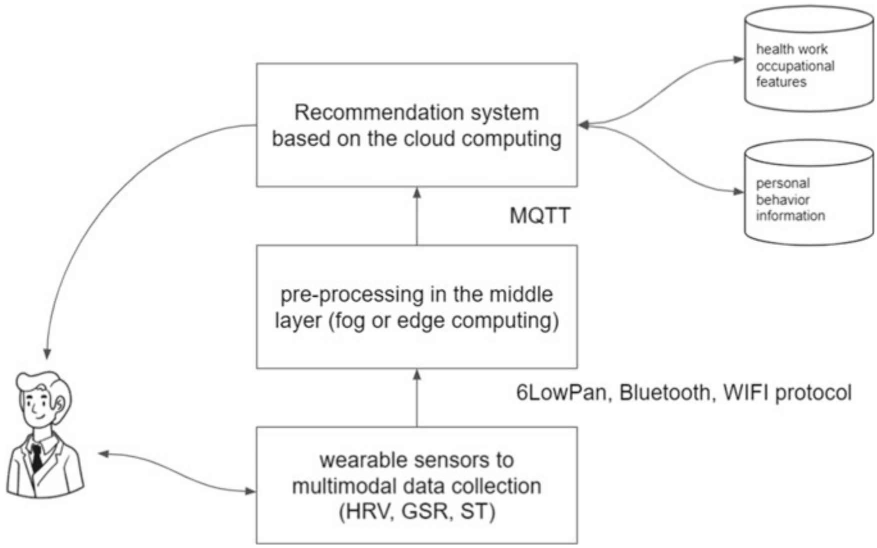

Fig. 2 IoT architecture proposal to biomarkers collection and communication system

in the cloud, make recommendations and send them directly to a mobile device of the people being monitored.

4.2 Stress Classification

In the scientific literature, there are different works that compare stress classification with the use of different techniques in various types of work activities; many of these works employ machine learning algorithms, statistical probability algorithms, fuzzy logic, and neural networks. For example, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), Fuzzy Logic, and Artificial Neural Networks (ANN). Some of these works make comparisons between the algorithms and results presented, as is the case of [38, 40]. In this scientific investigation, a classification solution that does not point only to the presence or absence of stress is sought. As proposed in [41], the presence or absence of stress is not sufficient to support the recommendation system. For example, the statistical method proposed in [38] presents 95% accuracy for the use of the GSR (stress classification with only one biomarker for vehicle driving activity), employing two levels of stress for each segment of the experiment, considering two levels for low, two levels for medium, and two levels for high stress. To develop a surveillance system for health professionals, different levels of stress identification will be needed. A survey of stress conditions and their biomarkers in frontline professionals will be done using appropriate sensors in the project's next stage. How the different biomarkers may be associated or interrelated to identify different levels of stress considering that a rating scale can be made. Furthermore, based on this information, the system proactively points out a recommendation for the stressful situation. With the selected biomarkers, it will be possible to predict a scale ranging from the lowest stress to the highest stress level. Works using scales to identify stress were found in [28, 42].

The following biomarkers should compose individual features that are important for determining scale within the system:

- • HRV with low and high frequencies, indicating stress or non-stress levels. This parameter can be used by frequency.
- • GSR presence or absence of stress through skin conductance.
- • ST (Skin Temperature)—skin temperature, inversely proportional to stress.

Combining the above parameters with periods in which these conditions are repeated in everyone, it is still possible to differentiate between acute and chronic stress. Furthermore, store individual records with the history of each monitored individual. Estimating the length of this time will also be an exciting research task. It can help identify the duration of the period of occupational stress and its relationship with the psychological and social conditions of the work environment. It predicted the use of recommendation systems techniques [14] because this type of monitoring generates a large volume of information. In other words, this type of system needs computational resources to process and assist in identifying stress and generating a set of recommended actions to prevent an early worsening of the stress situation. Perhaps the most significant difficulty in modeling the system is to propose an acceptable scale for classifying occupational stress levels for health professionals working on the pandemic's front lines. These data can only be proven after acquiring and collecting data from professionals working on the front line. It is also estimated that the classification may have a data validation mechanism (considering the individuality of the biomarkers) through questions and answers carried out by the system to certify the validity of the data indicated by the device.

Through this research, a system capable of identifying at least five levels of individual conditions is estimated, associating the different types of biomarkers and other features of labor occupation. Figure 3 illustrates the acquisition of signals on biomarkers, where it is possible to identify the layers of the IoT healthcare and the systemic structures necessary for the extraction of features and later classify the stress into five levels. It is essential to point out that the figure is illustrative and only demonstrates the flow of individual information from the biomarkers.

4.3 Recommendation Systems with Deep Learning

Recommendation systems emerged in the e-commerce area and advanced to other areas because they present a great way to process a high volume of data and associate recommendation responses to specific user profiles. They can be associated with different techniques, including deep learning to assist in the decision-making

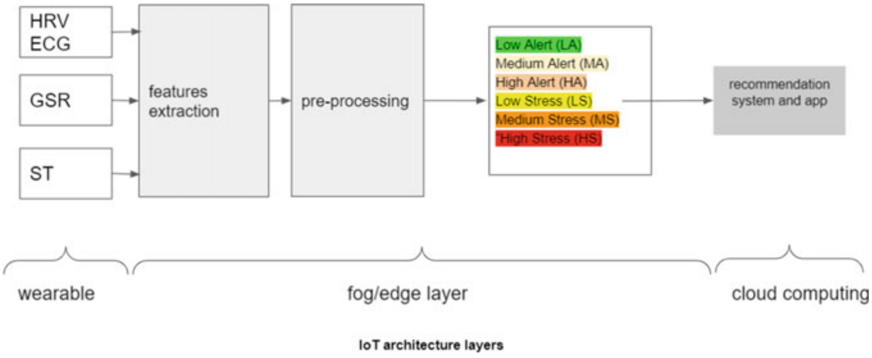

Fig. 3 Levels for identification of health workers' occupational stress

process in the medical field [39]. Recommendation systems can make predictions about user consumption. Likewise, there are similar scenarios in the health area where there is an immense amount of data to be processed and analyzed and all the personification of users who work in these environments. As is the case with the medical field and health professionals in a hospital, in this case, it is possible to identify different professionals with different working hours and specific activities. For example, doctors, nurses, nutritionists, physiotherapists, speech therapists, nutritionists, nursing technicians, radiologists, and other people linked to cleaning sectors and other hospital administrative activities. All these professionals may be suffering from different stress conditions due to their work activities due to the Covid-19 pandemic. It is a highly complex problem to automatically measure and assess occupational stress for these different categories. Recommendations should be personalized. In this case, the recommendation system should employ deep learning techniques to identify these different categories in the processing of information related to stress and how to point out to users how to face the situation so that it does not become a more serious situation and a case of seeking help from professionals. Hybrid recommendation systems are the most suitable for this high number of categories with different features and the information processed by sensors that are individual information of each professional [12]. Each of these professionals has a specific working day, working closer to the sectors of Covid-19, considering those who directly serve the ICUs and hospital wards with access to patients with Covid-19. All these factors are stressors and should be considered, in addition to individual biomarker measurements.

Figure 4 presents important points from the systemic view and some samples about the health workers' occupational information that has some influence on the distress condition.

The complexity of the problem requires using a more robust technique so that the results are better suited to the classification solution, such as in the case of deep learning. Furthermore, the modeling points out multimodal characteristics for the problem in question. Deep learning techniques are more appropriate for feature

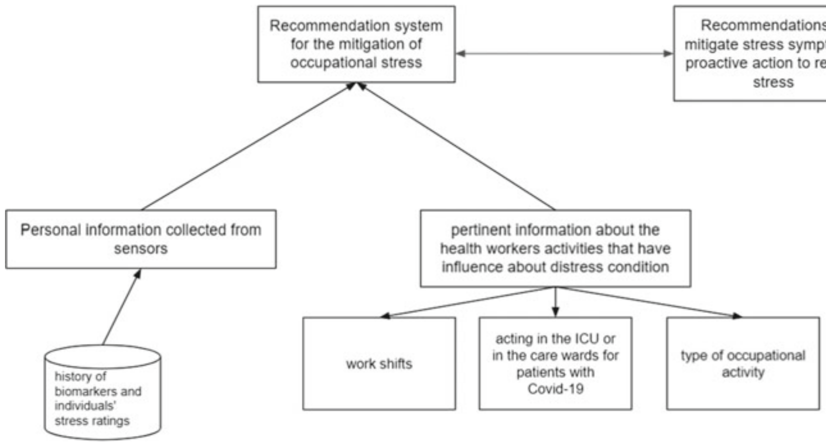

Fig. 4 Recommendation system architecture and interactions preview

extraction and knowledge representation, as traditional machine learning techniques are not effective for such complex situations. However, about training, a much larger volume of data is required for these techniques to present good results [43]. This is a new and unprecedented study in which the techniques to be employed must be unsupervised to present a classification scale according to the values of the input sensors and other information used to identify stress conditions. This encourages the use of techniques such as neural networks with recurrent characteristics so that the parameters reported by the sensors can be correlated with the information on the occupations of each individual. They imagined that each individual would have associated a set of biomarker features and a set related to their work occupation. The importance of using explainable techniques for the development of this type of system is also highlighted. The ability to explain how the algorithm works or how a decision is being recommended is considered essential for this type of solution to be implemented in a hospital network. This information is essential for the community to accept the use of these mechanisms and systems in real environments, as it has the ability to help understand how the system arrived at given reasoning, facilitating the acceptance of the results. Thus, increasing the reliability of IoT healthcare applications. That is, the solution to stress checking should not be a black box learning process. Some studies point to using new algorithms that help in the mapping of information and aid in decision-making processes [44, 45]. The solution needs to combine different Artificial Intelligence techniques that point the way through explainable reasoning different from the studies investigated so far. Moreover, the second issue concerns data protection, privacy, and security within the system [46, 47]. This is another critical point for the system to leave modeling for a real application environment. Having been adopted in Brazil, the general legislation on data protection is one of the points included in the model. The possibility of associating blockchain techniques in the system solution has been studied.

The multidisciplinary project team will develop the recommendations. For example, the system may recommend meditation and relaxation activities or outdoor physical activities by identifying lower stress levels. In identifying symptoms of distress, it should be recommended to seek help from a qualified professional to conduct a more specific treatment. This system, in the future, in addition to helping professionals deal with stress, should be able to map the mental health conditions related to occupational stress of professionals working on the front lines. It is a tool designed to support managers of health units to help identify the conditions of the professional team and support the definition of the team's work schedule.

5 Conclusion

This chapter presented a theoretical study on the main biomarkers for identifying occupational stress in health professionals who are facing the front line of the Covid-19 pandemic. The survey of this information is part of a research conducted by members of the Research Group on Intelligent Systems Applied to Health/CNPq/Brazil, which can be used in an IoT healthcare mechanism. These are the preliminary results of modeling a recommendation system for occupational stress surveillance in health professionals, which is currently underway, in cooperation with the institutions Federal University of Health Sciences of Porto Alegre (UFCSPA) and Federal University of Santa Catarina (UFSC). As a future work, this model is going to be integrate in a recommender system aiming to proactively propose mitigation actions in the surveillance of occupational stress of these professionals.

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References

1. Nie, A., Su, X., Zhang, S., Guan, W., Li, J.: Psychological impact of COVID-19 outbreak on frontline nurses: a cross-sectional survey study. J. Clin. Nurs. **29**(21–22), 4217–4226 (2020). https://doi.org/10.1111/jocn.15454
2. Chen, W., Huang, Y.: To protect health care workers better, to save more lives with COVID-19. Anesth. Analg. **131**(1), 97–101 (2020). https://doi.org/10.1213/ANE.0000000000004834
3. Paterlini, M.: On the front lines of coronavirus: the Italian response to covid-19. BMJ m1065 (2020). https://doi.org/10.1136/bmj.m1065
4. Ji, Y.D., Robertson, F.C., Patel, N.A., Peacock, Z.S., Resnick, C.M.: Assessment of risk factors for suicide among US health care professionals. JAMA Surg. **155**(8),. 713 (2020). https://doi.org/10.1001/jamasurg.2020.1338
5. Souza, R.C., Silva, S.M., Costa, M.L.A. de S.: Occupational stress in hospital settings: review of coping strategies of nursing professionals (Estresse ocupacional no ambiente hospitalar: revisão das estratégias de enfrentamento dos trabalhadores de Enfermagem). Rev. Bras. Med. Trab. **16**(4), 493–502 (2018). https://doi.org/10.5327/Z1679443520180279

6. W. H. Organization: State of the world's nursing 2020: investing in education, jobs and leadership. World Health Organization (2020) Disponível em: https://apps.who.int/iris/handle/10665/331677. Accessed 02 June 2021
7. Jalili, M., Niroomand, M., Hadavand, F., Zeinali, K., Fotouhi, A.: Burnout among healthcare professionals during COVID-19 pandemic: a cross-sectional study. Int. Arch. Occup. Environ. Health (2021). https://doi.org/10.1007/s00420-021-01695-x
8. Hong, S. et al.: Immediate psychological impact on nurses working at 42 government-designated hospitals during COVID-19 outbreak in China: a cross-sectional study. Nurs. Outlook **69**(1) 6–12 (2021). https://doi.org/10.1016/j.outlook.2020.07.007
9. Coghi, P.F., Coghi, M.F.: Stress e ansiedade: eles estão te consumindo?. In: 14° Congresso de Stress do ISMA, p. 13 (2013)
10. Koh, D.: Occupational risks for COVID-19 infection. Occup. Med. **70**(1), 3–5 (2020). https://doi.org/10.1093/occmed/kqaa036
11. Dar, M.N., Akram, M.U., Khawaja, S.G., Pujari, A.N.: CNN and LSTM-based emotion charting using physiological signals. Sensors **20**(16), 4551 (2020). https://doi.org/10.3390/s20164551
12. S. Zhang, Yao, L., Sun, A., Tay, Y.: Deep learning based recommender system: a survey and new perspectives. ACM Comput. Surv. **52**(1), 1–38 (2019). https://doi.org/10.1145/3285029.
13. Koldijk, S., Neerincx, M.A., Kraaij, W.: Detecting work stress in offices by combining unobtrusive sensors. IEEE Trans. Affect. Comput. **9**(2), 227–239 (2018). https://doi.org/10.1109/TAFFC.2016.2610975.
14. Batmaz, Z., A. Yurekli, Bilge, A., Kaleli, C.: A review on deep learning for recommender systems: challenges and remedies. Artif. Intell. Rev. **52**(1), 1–37 (2019). https://doi.org/10.1007/s10462-018-9654-y.
15. Ruotsalainen, J., Verbeek, J., Marin, A.é, Serra, C.: Preventing occupational stress in healthcare workers. Cochrane Database Syst. Rev. **134** (2014). https://doi.org/10.1590/1516-3180.20161341T1.
16. Marine, A., Ruotsalainen, J.H., Serra, C., Verbeek, J.H.: Preventing occupational stress in healthcare workers. In: Cochrane Database of Systematic Reviews, The Cochrane Collaboration, Org. Chichester, p. CD002892.pub2. Wiley, UK (2006). https://doi.org/10.1002/14651858.CD002892.pub2.
17. Horta, R.L. et al.: O estresse e a saúde mental de profissionais da linha de frente da COVID-19 em hospital geral. J. Bras. Psiquiatr. **70**, 30–38 (2021) https://doi.org/10.1590/0047-2085000000316
18. de Miyazaki, M.C.O.S., Soares, M.R.Z.: Estresse em profissionais da saúde que atendem pacientes com COVID-19. Soc. Bras. Psicol. (2021). Disponível em: https://www.sbponline.org.br/enfrentamento-covid19
19. Schabracq, M.J., Winnubst, J.A.M., Cooper, C.: The Handbook of Work and Health Psychology. Wiley, New York (2003)
20. Michie, S., Williams, S.: Reducing work related psychological ill health and sickness absence: a systematic literature review. Occup. Environ. Med. **60**(1), 3–9 (2003). https://doi.org/10.1136/oem.60.1.3
21. Lizano, E.L.: Examining the impact of job burnout on the health and well-being of human service workers: a systematic review and synthesis. Hum. Serv. Organ. Manag. Leadersh. Gov. **39**(3), 167–181 (2015). https://doi.org/10.1080/23303131.2015.1014122
22. de Carvalho, L., Malagris, L.E.N.: Avaliação do nível de stress em profissionais de saúde. Estud. E Pesqui. Em Psicol. **7**(3), 0–0, dez. 2007
23. Sharma, N., Gedeon, T.: Objective measures, sensors and computational techniques for stress recognition and classification: a survey. Comput. Methods Programs Biomed. **108**(3), 1287–1301 (2012). https://doi.org/10.1016/j.cmpb.2012.07.003
24. Universidade de São Paulo et al.: Os biomarcadores como tendência inovadora para auxiliar no diagnóstico de doenças mentais em trabalhadores. Rev. Bras. Med. Trab. **16**(3), 371–377 (2018). https://doi.org/10.5327/Z1679443520180234
25. Gupta, M., Vaikole, S.: Recognition of human mental stress using machine learning paradigms. SSRN Electron. J. (2020). https://doi.org/10.2139/ssrn.3571754

26. Pagliarone, A.C., Sforcin, J.M.: Estresse: revisão sobre seus efeitos no sistema imunológico. **11**(1), 34 (2009)
27. Surangsrirat, D., Dumnin, S., Samphanyuth, S.: Heart rate, skin temperature and skin humidity and their relationship to accumulated fatigue. In 2019 3rd International Conference on Bio-engineering for Smart Technologies (BioSMART), Paris, France, pp. 1–4 (2019). https://doi.org/10.1109/BIOSMART.2019.8734230
28. Han, L., Zhang, Q., Chen, X., Zhan, Q., Yang, T., Zhao, Z.: Detecting work-related stress with a wearable device. Comput. Ind. **90**, 42–49 (2017). https://doi.org/10.1016/j.compind.2017.05.004
29. Ahn, J.W., Ku, Y., Kim, H.C.: A novel wearable EEG and ECG recording system for stress assessment. Sensors **19**(9) (2019). https://doi.org/10.3390/s19091991
30. Hashmi, A., Yadav, S.K.: A systematic review of computational methods for occupational stress modeling based on subjective and objective measures. Int. J. Comput. Sci. Eng. **6**(6), 456–470 (2018). https://doi.org/10.26438/ijcse/v6i6.456470
31. Jovanov, E., Frith, K., Anderson, F., Milosevic, M., Shrove, M.T.: Real-time monitoring of occupational stress of nurses. In: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Boston, MA, pp. 3640–3643 (2011). https://doi.org/10.1109/IEMBS.2011.6090612
32. Djuric, Z., et al.: Biomarkers of psychological stress in health disparities research. Open Biomark. J. **1**(1), 7–19 (2008). https://doi.org/10.2174/1875318300801010007
33. Patil, K., Singh, M., Singh, G., Sharma, N.: Mental stress evaluation using heart rate variability analysis: a review. **2**(1), 8
34. Guo, H.-W., Huang, Y.-S., Lin C.-H., Chien, J.-C., Haraikawa, K., Shieh, J.-S.: Heart rate variability signal features for emotion recognition by using principal component analysis and support vectors machine. In: 2016 IEEE 16th International Conference on Bioinformatics and Bioengineering (BIBE), Taichung, Taiwan, pp. 274–277 (2016). https://doi.org/10.1109/BIBE.2016.40
35. Affanni, A.: Wireless sensors system for stress detection by means of ECG and EDA acquisition. Sensors **20**(7), 2026 (2020). https://doi.org/10.3390/s20072026
36. Thayer, J.F., Åhs, F., Fredrikson, M., Sollers, J.J., Wager, T.D.: A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neurosci. Biobehav. Rev. **36**(2), 747–756 (2012). https://doi.org/10.1016/j.neubiorev.2011.11.009
37. Herborn, K.A., et al.: Skin temperature reveals the intensity of acute stress. Physiol. Behav. **152**, 225–230 (2015). https://doi.org/10.1016/j.physbeh.2015.09.032
38. Memar, M., Mokaribolhassan, A.: Stress level classification using statistical analysis of skin conductance signal while driving. SN Appl. Sci. **3**(1), 64 (2021). https://doi.org/10.1007/s42452-020-04134-7
39. Morales, A.S., Ourique, F. de O., Cazella, S.C.: A comprehensive review on the challenges for intelligent systems related with internet of things for medical decision. In: Marques, G., Kumar Bhoi, A., de la Torre Díez, I., Garcia-Zapirain, B. (Eds.), Enhanced telemedicine and e-health: advanced IoT enabled soft computing framework, pp. 221–240. Springer International Publishing, Cham (2021). https://doi.org/10.1007/978-3-030-70111-6_11
40. Gul Airij, A., Bakhteri, R., Khalil-Hani, M.: Smart wearable stress monitoring device for autistic children. J. Teknol. **78**(7–5) (2016). https://doi.org/10.11113/jt.v78.9453
41. Alic, B., Sejdinovic, D., Gurbeta, L., Badnjevic, A.: Classification of stress recognition using Artificial Neural Network. In: 2016 5th Mediterranean Conference on Embedded Computing (MECO), Bar, Montenegro, pp. 297–300 (2016). https://doi.org/10.1109/MECO.2016.7525765
42. Liu, Y., Du, S.: Psychological stress level detection based on electrodermal activity. Behav. Brain Res. **341**, 50–53 (2018). https://doi.org/10.1016/j.bbr.2017.12.021
43. Nweke, H.F., Teh, Y.W., Al-garadi, M.A., Alo, U.R.: Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges. Expert Syst. Appl. **105**, 233–261 (2018). https://doi.org/10.1016/j.eswa.2018.03.056

44. Murdoch, W.J., Singh, C., Kumbier, K., Abbasi-Asl, R., Yu, B.: Interpretable machine learning: definitions, methods, and applications. Proc. Natl. Acad. Sci. **116**(44), 22071–22080 (2019). https://doi.org/10.1073/pnas.1900654116
45. Tjoa, E., Guan, C.: A survey on explainable artificial intelligence (XAI): towards medical XAI. IEEE Trans. Neural Netw. Learn. Syst. 1–21 (2020). https://doi.org/10.1109/TNNLS.2020.3027314
46. Qadri, Y.A., Nauman, A., Zikria, Y.B., Vasilakos, A.V., Kim, S.W.: The future of healthcare internet of things: a survey of emerging technologies. IEEE Commun. Surv. Tutor. **22**(2), 1121–1167 (2020). https://doi.org/10.1109/COMST.2020.2973314
47. Allaert, F.-A., Mazen, N.-J., Legrand, L., Quantin, C.: The tidal waves of connected health devices with healthcare applications: consequences on privacy and care management in European healthcare systems. BMC Med. Inform. Decis. Mak. **17**(1), 10 (2017). https://doi.org/10.1186/s12911-017-0408-6

The Experience of Diagnosis and Management of Oral Maxillofacial Surgery, and Dental Education During the Pandemic

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Abstract During the process of diagnosis and treatment of patients, medical staff in oral and maxillofacial surgery are prone to infection through respiratory droplets transmission and close contact with the infected person. Therefore, precise epidemic prevention and control measures must be taken during daily diagnosis and treatment, and oral and maxillofacial surgeries should be carried out in an orderly manner to reduce the risk of infection as much as possible. In addition, in order to ensure the quality of resident training, it is necessary to actively utilize the hospital's modern educational technology and expand new training models. Through e-learning teachers can convert educational resources into e-content, trying to make it engaging so as to enhance student motivation. As most dentistry training is conducted in clinical setting it is necessary to apply all the resources provided by digital technologies in order to improve distance learning for students.

Keywords Oral maxillofacial surgery · Dental informatics · Education · Pandemic

1 The Importance of Technology in Dental Education During the Pandemic

Preventive measures to contain the spread of the COVID-19 pandemic have initiated the closure of educational institutions around the world, impacting over 90% of the world's student population. In their efforts to mitigate the immediate impact of school closures, many universities and faculties have replaced the traditional methods with

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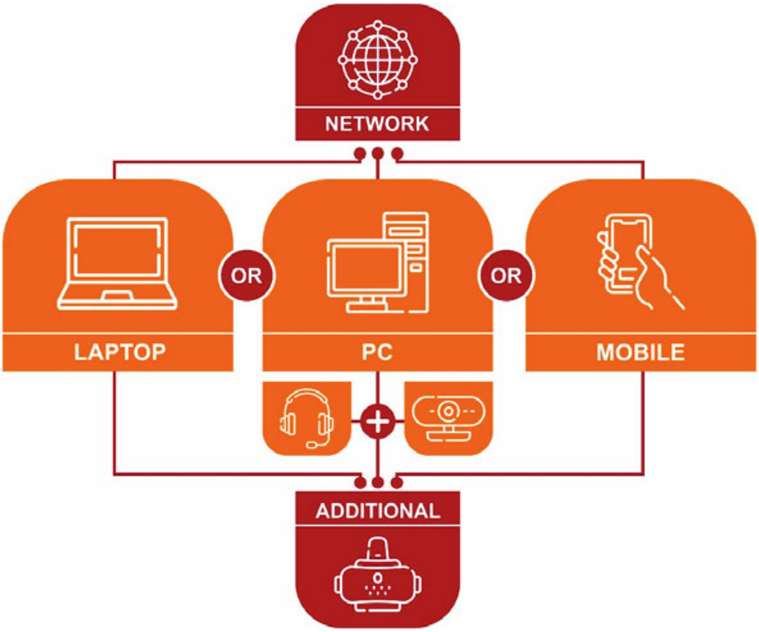


Fig. 1 Necessary equipment for e-learning (Image by the author)

distance learning. Distance learning has been based primarily on electronic communication between students and teachers, i.e. on e-learning. E-learning is defined as the provision of educational content through the media based on the computer and its networks to the recipient (Fig. 1). This way teachers can visually present educational content in a technology-based environment, so as to arouse the interest of students. [8]. Students, on the other hand, can learn at the desired pace [19].

Since dentistry is more demanding compared to other branches of medicine in that a large part of practical training requires interaction with a patient, it is necessary to apply all resources in additional education to improve student's understanding of certain clinical procedures outside clinical practice. To this end, a number of advantages provided by digital technologies are applied.

1.1 Lectures/Problem Based Learning

As it regards the provision of theoretical knowledge, it was rather easy to switch to online learning with the help of electronic learning platforms. One of these is Moodle®—a free teaching tool with a simple interface that has been widely used during the pandemic. Its advantages are reflected in the simple posting of teaching material (presentations, video and audio material), the possibility of discussion and evaluation of student progress. However, Moodle® does not allow live communication between users, which being extremely important, highlighted the efficacy of open and paid online learning platforms such as ZOOM®, Google Classroom®, Skype®, etc. These tools enable good interaction between users but they require daily improvements, maintenance, and stable internet connection [1, 6]. In addition to the mentioned e-learning platforms, social networks were of great importance in the transfer of knowledge during the pandemic, enabling easy communication between users and rapid file-sharing (Instagram®, Facebook®, WhatsApp®, Viber®, Telegram®, and YouTube®).

In addition to student education, e-learning has found application in continuing dental education programs; conferences and symposia have been conducted via webinar technology. Webinars are online learning tools the main feature of which is personalized learning environment with lower costs and access to online content for users who have not been able to watch live broadcasts [2].

1.2 Dedicated Applications

With numerous entertainment-oriented applications available online, teachers have a challenging task in finding creative ways to display educational content. One of them is the creation of dedicated applications for educational purposes. These are particularly valuable in situations that are not ordinary in daily dental practice, such as managing dental trauma (Traumatic Dental Injuries—TDI) the training of which is of particular importance in dentistry studies [3]. During pandemic a step by-step mobile application for managing traumatic dental injuries was developed. Mobile learning resulted in improved knowledge of dental traumatology diagnostics and treatment, and students of other dental disciplines showed a preference in having this method of learning as part of the curriculum [8, 11]. In addition to training in management of TDIs, rarely encountered in student practice, local anesthesia training is of great importance as this is a routine procedure in dermatological practice. The application of local anesthesia requires a thorough knowledge of the anatomy of the orofacial region, thus it is very important that the student understands the concepts of the procedure and develops fine motor skills to implement it [14]. Due to the impossibility of conducting conventional classes for learning local anesthesia, which was based on exercise on plastic models and jawbones, 3D simulation was used. In addition to learning at one's own pace this method of distance learning is supported by the fact that the human brain operates on the principle of images and associations; the fastest and easiest way it adopts content is through images, that is, through a visual experience [9] (Fig. 2).

The benefits of 3D technology in dental education during the pandemic have also been demonstrated by Mahrous et al. [7] who have developed a useful platform for learning tooth morphology. In addition to improving the 3D spatial understanding of tooth structure, the use of virtual models has advantages over natural

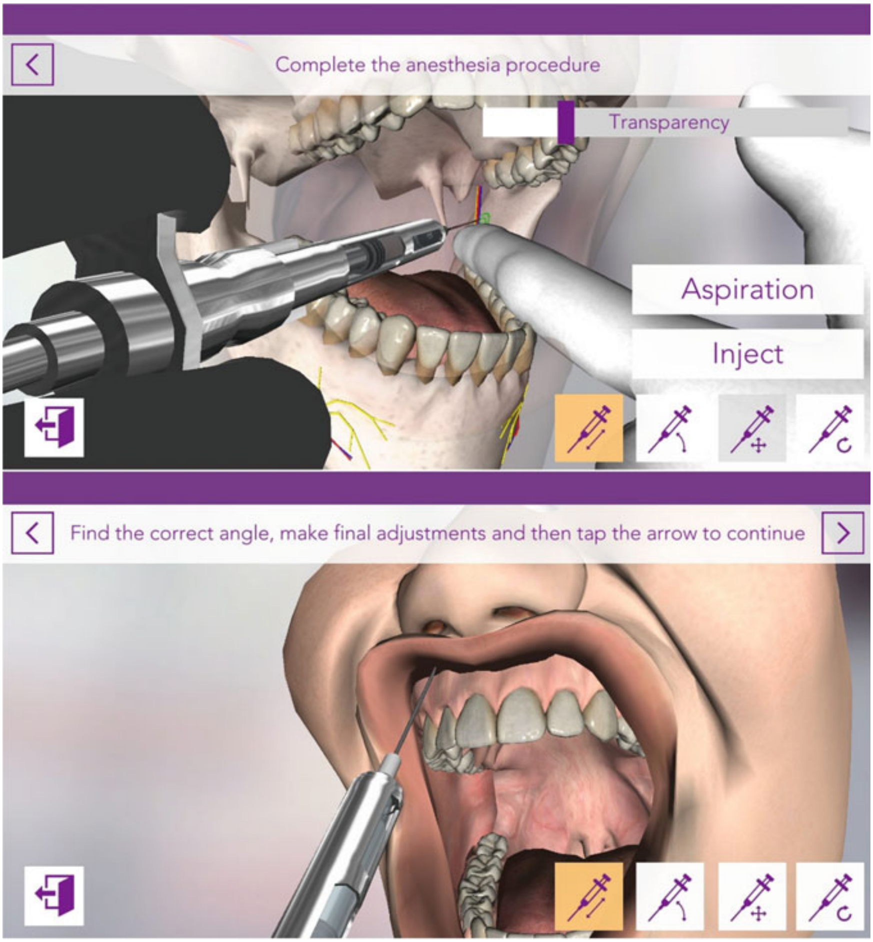


Fig. 2 Simulation of local anesthesia in a 3D environment (Image by the author)

teeth because they are often damaged and require restoration before use for educational purposes. To tackle the problem of absence of a dental laboratory during the pandemic, Giugliano et al. [4] established a platform on artificial teeth arrangement for a complete denture. The platform does not require any software installation or purchase by students; it allows students to work independently and have unlimited practice, while the automated grading provides an efficient measure, which is of special importance during remote instruction.

Dedicated educational applications are an excellent way to improve students' motivation, given the high level of engagement and novelty, personalization and autonomy. These technological resources provide ease of access to information, reusable resources, training, and upgrade of procedures or techniques.

1.3 Virtual Reality and Augmented Reality

Virtual Reality (VR) is a computer-generated environment that allows users to immerse themselves in the "virtual world" through visual, auditory, tactile and olfactory sensations, making the VR experience different from watching television or playing video games. Initially, VR was used in entertainment industry exclusively; with the development of Oculus Rift in 2012, and the launch of Google Cardboard in 2014, the application of VR in education and training came into focus [12]. Dental education is the discipline that could benefit the most from VR, as a significant portion of preclinical dental education is dedicated to teaching psychomotor clinical skills [21]. But despite its great potential, this technology has not found widespread use during the pandemic. Only one study has dealt with the application of VR technology in dental education during the COVID-19 pandemic [22]. The main reason is that VRSs are immobile, expensive and require equipment not readily available for use at home [5].

Although it requires more sophisticated devices, augmented reality (AR) is less immersive than VR. The reason is that it enhances the existing environment by adding virtual elements, rather than replacing it with a completely new environment. (AR is 25% virtual and 75% real) [12]. AR enhances students' engagement by providing unparalleled interactive experiences in a computer-generated environment. Mladenovic et al. [13] have examined the effect of using an AR simulator in mandibular anesthesia training during pandemic (Fig. 3). This type of learning enables great user interaction and training on a virtual patient, thus improving manual dexterity of dentistry students. The special significance of this technology is that it that it allows for 3D planning of the procedure. Using the augmented reality technique, anatomical structures in the oral cavity and anatomic reference points are simpler for localization and identification [15]. It is important to note that no additional expensive devices are needed for the AR simulator to function. All you need is a mobile phone or tablet and AR markers (which are usually printed on paper), this being one of the main potentials of this technology.

The time of VR and AR technologies is yet to come; they can contribute to the progress of the traditional education system by transforming the entire learning experience. Currently, the focus is on creating quality educational content and finding ways to effectively implement these new educational technologies in teaching. The lack of computer skills of teachers is currently a significant obstacle in the development of educational applications, which negatively affects the wider use of these technologies as learning tools.

1.4 Final Considerations

e-learning has become a convenient tool for the progress of education, and it has received special attention during distance learning during a pandemic. In the fight

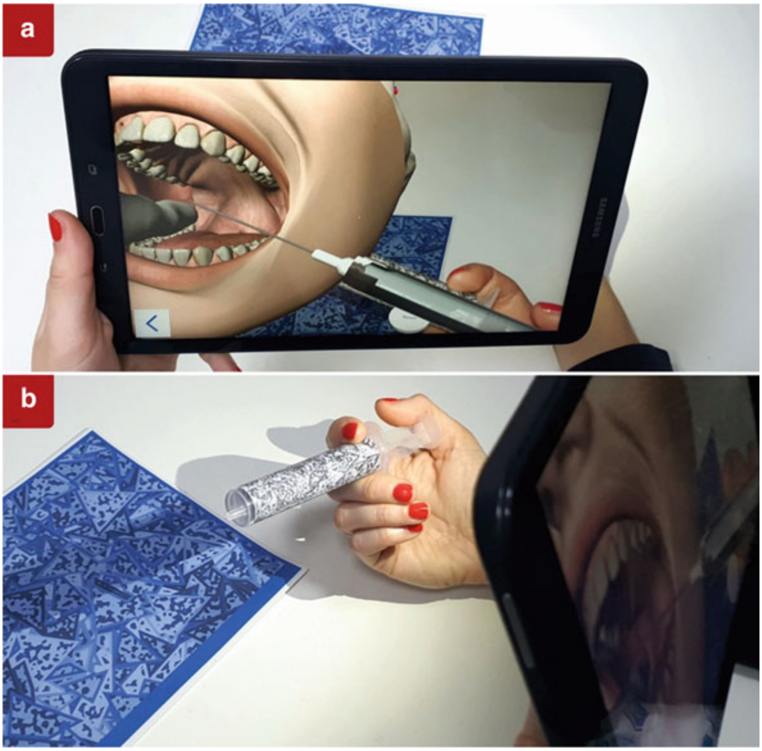


Fig. 3 Administering local anesthesia for inferior alveolar nerve block in Augmented Reality environment (panel A—student sees; panel B—environment sees) (Image by the author)

for attention, science has competitors in the entertainment and leisure industry, and in order to improve the transfer of knowledge, it is necessary to include all the resources provided by new technologies. It is very important that teachers keep up with the times, thus addressing the interests of students [10]. E-learning methods provide more open access to educational content and continuous learning [6, 16], as well as additional flexibility because they allow students to explore the content at their own pace and dive deeper into what is most interesting to them. However, despite all the advantages of digital technologies, none of them can replace the experience that students gain in interaction with real patients.

2 The Experience of Diagnosis and Management of Oral and Maxillofacial Surgery Patients During COVID-19 Pandemic

The New Coronavirus 2019 (2019-ncov) that first emerged in late 2019 has spread globally. The virus is highly contagious and generally all ages of the population appear to be susceptible SARS-cov-2 infection, and this has resulted in a worldwide pandemic of coronavirus disease 2019 (COVID-19). SARS-cov-2 is predominantly spread from person-to-person, it is infectious during the incubation period and highly contagious in the first 5 days after symptom onset. The modes of transmission include: (1) Respiratory droplets transmission and close contact with the infected person are the primary mode of transmission, transmission can also occur via indirect contact with the contaminated surfaces or objects; (2) Airborne transmission may also occur in circumstances or settings that generate aerosols; (3) As SARS-CoV-2 RNA could be detected in feces and urine samples, appropriate precautions should be implemented to prevent environment contamination and transmission of SARS-CoV-2.

As SARS-CoV 2 is transmitted mainly by exposure to infected respiratory droplets and close contact transmission, or through direct contact with blood and body fluids of the infected patients, the healthcare personnel of Department of Oral and Maxillofacial Surgery are especially vulnerable due to the close proximity to the oral and nasal cavities during procedures [20]. Besides, the routine procedures in oral and maxillofacial surgery including endotracheal intubation, tracheostomy, airway suctioning, and oral irrigation are generally aerosol-generating procedures (AGPs) In view of the healthcare workers are at increased risk for contracting COVID-19, it is important to triage the patients and to execute strict adherence of cross infection control and use of personal protective equipment (PPE) [29]. In addition, COVID-19 has brought challenges to the original standardized offline training mode for residents. In order to ensure the safety of residents and minimize the impact of the epidemic on residents, it is necessary to actively utilize the modern educational technology conditions of hospitals to expand the new training mode.

2.1 Intern Education of Oral and Maxillofacial Surgery

The Coronavirus disease 2019 (COVID-19) pandemic has had immense impact in residency training programs of oral and maxillofacial surgery residency. As the patient admissions mainly focused on emergent and urgent cases and elective cases of other sub-specialties of oral and maxillofacial surgery were postponed during this crisis, therefore, the residents' clinical exposure and clinical skills were significantly restricted. Besides, certain residents were unable to attend clinical training in the hospital during the lockdown period. Despite of problems and challenges encountered, the department is dedicated in ensuring continuation of residency training programs.

Didactic lectures, which are part of the educational component of residency training program, were recorded in the form of videos and conducted through online learning platform to adhere to social distancing recommendation during this pandemic, allowing the residents to continue their learning process. While the residency training programs also include clinical hands-on training, the COVID-19 pandemic has resulted in substantial decline in numbers of relevant clinical cases, and some residents were unable to attend due to the lockdown measures. Hence, lecturers created educational videos from previously recorded surgical demonstration videos on "Open reduction and internal fixation of mandibular fracture", "superficial parotidectomy" and other classical surgical demonstration to allow effective online learning.

Through videoconferencing software such as Tencent Meeting and Zoom Meeting, virtual ward rounds and case discussion can be conducted. Residents were engaged through the online case presentation and journal club, while senior consultants were present to guide the clinical discussion. High-resolution video and audio technologies provided clear display of patients' pathology, allowing effective clinical teaching through live streamed ward round. Online meeting platform enabled residents to observe classical clinical cases during virtual ward round and formulate case presentations for subsequent case-based discussion in small groups, thus creating an effective clinical teaching session. Regular and structured online case discussions and virtual ward round had provided active learning opportunities during the pandemic.

With the strict adherence to cross infection control and adequate use of personal protective equipment (PPE), residents were allowed to continue routine clinical duties in emergency department or to attend urgent procedures. During the COVID-19 outbreak, most of the surgical procedures prioritized were emergent surgical procedures including open reduction and internal fixation (ORIF) of maxillofacial fractures, incision and drainage of maxillofacial space infection, surgical resection and reconstruction in malignant maxillofacial tumors. Such learning opportunities were especially cherished as residents were able to fulfill clinical training while helping the patients during this pandemic.

2.2 Triage of Patients

The patients in oral and maxillofacial surgery can be triaged based on the urgency and severity, including critically ill patients, subacute patients, patients who require expeditious interventions and patients requiring elective procedures. During the control and prevention phase of COVID-19, the patient admission is prioritized based on the urgency and severity.

2.2.1 Critically ill patients: patients who require emergency surgical interventions or procedures due to life threatening conditions such as hemorrhage and obstruction of upper respiratory tract following trauma, tumors or infections.

2.2.2 Subacute patients: patients with stable vital signs requiring urgent interventions, including closed fractures and non-life-threatening maxillofacial space infections.

2.2.3 Patients who require expeditious interventions: patients diagnosed with malignant tumors and chronic infections, who require surgical interventions.

2.2.4 Patients who require elective procedures: adequate preoperative preparation should be done, and timing of surgery has no significant impacts, which include patients diagnosed with cleft lip and palate, dentofacial deformities and benign tumors.

2.3 Admission Protocol

Critically ill patients will be admitted directly, while the patient admission of the other three categories is dependent on the triage of the patients, the policies of higher authorities, the current and local epidemic situation and the allocation of medical resources. Pre-screening for COVID-19 is required prior to hospital admission.

2.3.1 Risk Assessment and Screening: Comprehensive Risk Assessment and Analysis Based on the Epidemiology, Clinical Presentation, Laboratory Test Results

2.3.1.1 Epidemiologic history taking: please note that the content is subject to change based on the actual pandemic situation. According to the COVID-19 Diagnosis and Treatment Guidelines (8th trial edition) [25]:

i. Travel or residence history at the infected area in the past 14 days;
ii. Contacts with confirmed COVID-19 cases (symptomatic or asymptomatic) in the past 14 days;
iii. Contacts with symptomatic individuals (e.g., Fever or upper respiratory infection symptoms) from the community with confirmed COVID-19 cases in the past 14 days;
iv. Cluster of cases, in which two or more confirmed cases with fever and/or upper respiratory infection symptoms, associated with the single facility, including living facility, workplace or school facility

2.3.1.2 Clinical presentation and laboratory testing.

Patients will be classified as suspected case of COVID-19 if they fulfill any one of the above epidemiologic criteria and fulfill any two of the clinical criteria; or if they fulfill any two of the clinical criteria and SARS-CoV 2 specific IgM antibody was tested positive; or if they fulfill any three of the clinical criteria.

i. History of travel or residence in community with confirmed cases within 14 days of onset;
ii. Fever and/or upper respiratory infection symptoms (dry cough, sore throat) and other relevant clinical presentations
iii. Chest Computed Tomography (CT) scan revealed multiple small patchy shadowing and interstitial changes, which are obvious at the periphery of the lungs. In severe cases, multiple ground glass opacification, infiltration appearance and lung consolidation can be seen in both lungs; in the early stage of the disease, the total white cell count is normal or decreased, and the lymphocyte count is normal or decreased.

2.3.1.3 Oropharyngeal or nasopharyngeal swab sample taken for Real-time reverse transcriptase-polymerase chain reaction (RT-PCR) for detection of SARS-CoV 2, in which a positive test is the gold standard for diagnosis [26].

2.3.1.4 The SARS-CoV 2 specific antibody test may serve as reference for diagnosis in individuals who have not been vaccinated. However, this test is not applicable to individuals who have been vaccinated or with history of past COVID-19 infection [26].

2.3.2 Hospital Admission Process

2.3.2.1 Via Emergency Department (ED): applicable to critically ill patients who required admission, in which the risk assessment, screening and vital signs measurements will be performed by attending doctor in ED while arranging for emergency operation. Risk assessment and screening should be completed as soon as possible, according to patient's physical conditions.

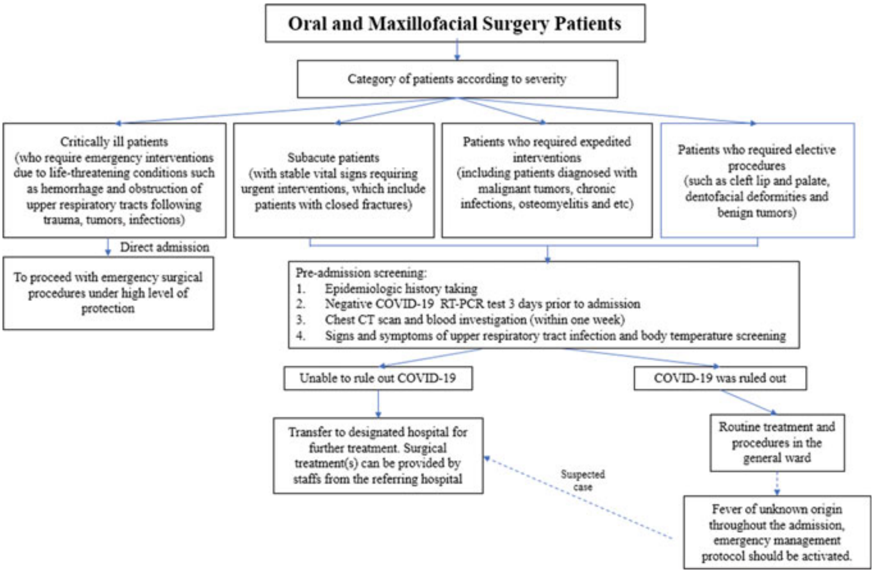
2.3.2.2 Via Outpatient Clinic: applicable to subacute patients, or patients requiring expeditious or elective procedures. Patients are required to complete the risk assessment and screening and fulfill the requirements below prior to hospital admission.

i. No epidemiologic risk factors;
ii. Relevant tests: Negative COVID-19 test 3 days prior to admission; Negative findings of chest CT scan within 1 week prior to admission (no obvious patchy shadowing and interstitial changes, no ground glass and infiltrative appearance and lung consolidation); Hematological test (normal or raised white cell count and lymphocyte count); Other relevant tests such as cardiac and lung function tests and polysomnography should be completed prior to hospital admission

during pandemic, in view of such investigations are not available in dental hospital. Patients are not allowed to leave the hospital facility after admission. Patients aged 60 years old and above are required to complete anesthetic preoperative assessment and patients with known cardiovascular or pulmonary diseases are required to complete Echocardiogram, lung function test. Patients are afebrile (temperature <37.3 °C), no fatigue of unknown cause, no upper respiratory tract infection symptoms such as dry cough, sore throat, congestion or runny nose.

Please note that patients who sustained trauma of maxillofacial region or diagnosed with maxillofacial space infection or malignant tumors are often febrile. Thus, it is important rule out COVID-19 through history taking, clinical presentation, hematological test and chest CT scan.

As dental hospitals are unable to provide treatments and management for COVID-19 patients, it is of utmost importance to practice standard precautions and isolation measures, and refer to the designated hospital, regardless of suspected or confirmed COVID-19 cases. See Flowchart 1, the algorithm of diagnosis and treatment for patients categorized according to the urgency and severity of the disease and interventions.



Flowchart 1 Algorithm of diagnosis and treatment for patients categorized according to the urgency and severity of the disease and interventions

2.4 Patient Management During Hospital Admission

2.4.1 Basic Facilities

2.4.1.1 Inpatient's elevators and walkways are designated for inpatient transport;

2.4.1.2 Wards should be well-ventilated, equipped with lavatories and sinks and/or alcohol-based hand sanitizers. Education and instruction on appropriate hand hygiene protocol are provided to both patient and escort (if present);

2.4.1.3 Preparation of isolation rooms or buffer areas.

i. Ensure adequate supplies of hospital-grade disinfectants and personal protective equipment (PPE) in response to acute respiratory infection cases;
ii. Dedicated for isolation or quarantine of suspected or pending cases;
iii. Critically ill patients who are not adequately screened prior to admission will be admitted to isolation room, and will be transferred to normal ward once COVID-19 has been ruled out;
iv. Patients developing fever of unknown origin or acute respiratory infection symptoms will be transferred to isolation room and crisis preparedness and response team will be activated;

2.4.2 Visitors are prohibited during the hospital admission, remote communications via telephone or video calls using internet connection are set up as alternatives.

2.4.3 Strict restriction on entry into wards: 24 h access control, temperature screening, history taking on epidemiologic data and health declaration are pre-requisite to enter the wards. Healthcare workers will be scheduled for regular COVID-19 testing and visiting is strictly prohibited.

2.4.2 Patient's Escort Services

2.4.4.1 Escort services are discouraged, except for activities of daily living (ADL) dependent patients one escort is allowed throughout the admission and the duration of escort should be minimized;

2.4.4.2 All escorts are required to complete COVID-19 risk assessment and screening (including epidemiologic history, health declaration and negative COVID-19 test 3 days prior) before entering the facilities.

2.4.4.3 Temperature screening and health declaration for signs and symptoms of upper respiratory tract infection for escorts will be conducted and recorded by staff nurses twice daily. Should the body temperature is $\geq$37.3 °C, or presented with upper respiratory tract infection symptoms, attending doctor and matron must be informed immediately to rule out COVID-19 and crisis preparedness and response team will be activated if necessary (Follow as 1.2.4.5).

2.4.4.4 Movement of escorts in the healthcare facility should be restricted. Escorts should only accompany the patients they are caring for during investigations and surgery throughout the admission.

2.4.4.5 Details of access to the facilities of both patient and escort, including time and reasons of entry or exit of the ward and mode of transport will be recorded. Temperature screening and health declaration will be recorded prior to entry.

2.4.3 Contingency Plan for Inpatients

If patients or escorts developed fever and/or upper respiratory tract infection symptoms (after completion of COVID-19 screening), further laboratory investigations should be performed, and clinical presentations should be correlated to rule out COVID-19. As postoperative fever is common following maxillofacial surgical procedures, detailed history taking, clinical examination, hematological test and chest CT scan should be performed to rule out COVID-19 if patients presented with similar signs and symptoms. However, if COVID-19 cannot be ruled out, or the signs and symptoms fulfill the clinical criteria of COVID-19, crisis preparedness and response team should be activated. The same protocol is applied to the patient's escort, if escort presented with fever and/or upper respiratory tract infection symptoms (See Flowchart 2).

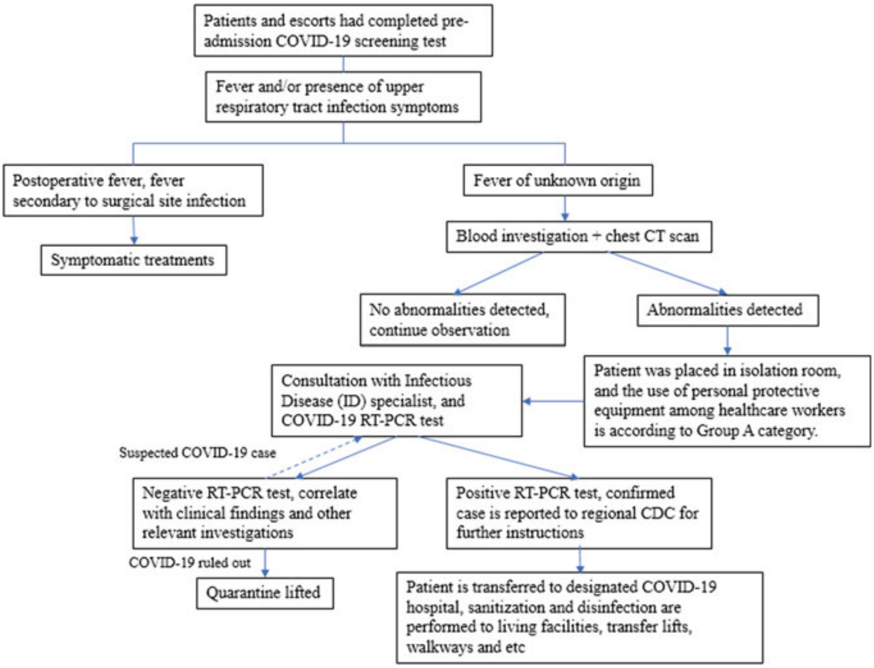
2.5 Personal Protection of Healthcare Personnel

As SARS-CoV 2 is highly contagious, the rational and appropriate use of personal protective measures during routine clinical practices should be selected based on the risk of exposure and transmission dynamics of the pathogen.

2.5.1 Categories of Surgical Patients:

2.5.1.1 Critically ill patients are divided into 3 groups [23]

I. Group A: Suspected or confirmed COVID-19 cases should be transferred to designated COVID-19 hospital, if circumstances permit; or individuals who cannot complete the screening for COVID-19 disease and requires immediate surgical intervention.
II. Group B: Negative COVID-19 test but presence of characteristic epidemiologic features or COVID-19 symptoms such as fever and/or upper respiratory tract infection or positive findings in chest imaging; or patients who had acquired COVID-19 in the past 4 weeks.
III. Group C: COVID-19 disease has been ruled out



Flowchart 2 Emergency procedures for patients or escorts developed fever and/or upper respiratory tract infection symptoms

2.5.1.2 Subacute patients, patients requiring expeditious or elective surgeries who have completed COVID-19 screening and COVID-19 disease has been ruled out, will be managed as according to Group C patients.

2.5.2 Personal Protective Measures

2.5.2.1 Refer Table 1 for the personal protective measures for operating theatre (OT) staffs and surgical patients [23].

2.5.2.2 In accordance with the ‘Technical Guidelines for Use of Protective Personal Protective Equipment for Healthcare Personnel for COVID-19 (Trial)’ [27], the clinical procedures were categorized into three categories based on the risk of exposure. (See Table 2).

Table 1 Personal protective measures for OT staffs and surgical patients

OT Staffs/ Patients	Hand hygiene	Single gloves	Double gloves	Surgical cap	Surgical scrubs	Surgical gowns	N95 masks	Medical surgical mask	Goggles/ face shield	Protective gowns	Hazmat suit	Shoes/ shoe covers
Surgeons, scrub nurses	ABC	C	AB	ABC	ABC	ABC	AB	C	AⒷⒸ	ⒷⒸ	A	AⒷ
Anesthetist, theatre nurses	ABC	BC	AⒷ	ABC	ABC	–	AB	C	AⒷⒸ	ABⒸ	A	AⒷ
Others	ABC	AⒷⒸ	–	ABC	–	–	AⒷⒸ	BC	ⒶⒷⒸ	ABⒸ	Ⓐ	AⒷ
Patients	–	–	–	ABC	Patient's gown	–	–	–	–	–	–	–

Note 1. A, B, C: recommended personal protective equipment (PPE), while, Ⓐ, Ⓑ, Ⓒare optional; 2. Medical surgical masks or N95 masks should be used in treating Group A and B patients, while medical surgical masks can be used when treating Group C patients; 3. Others: OT support workers including cleaners, porter and janitor; 4. Cleaning and disinfection are practiced based on the levels of contamination

Table 2 Classification and protection of common procedures in oral and maxillofacial surgical wards

Risk of exposure	Types of contacts and exposure	Relevant Procedures	Personal Protective Equipment									
			Hand Hygiene	Scrubs	Surgical caps	Surgical masks	N95 masks	Gloves	Disposable gowns	Hazmat suit	Face shields/Eye goggles	Plastic disposable overshoes
Low risk	Indirect contact	Health education, history taking, ward rounds, pre-operative consent taking	ABC	ABC	ABC	BC	AⒷ	A	A	–	Ⓒ	Ⓒ
Moderate risk	Direct contact with patients, non-aerosol generating invasive procedures	Physical examination, fine needle aspiration, injection, Electrocardiogram (ECG) monitoring, wound dressings, nebulization	ABC	ABC	ABC	BC	AⒷ	ABⒸ	Ⓑ	A	AⒷ	A
High risk	Normal patients with contacts and exposure to aerosol and body fluids	Nasopharyngeal and oral suctioning, oral irrigation and treatment, incision and drainage, wound irrigation, use of rotary handpiece system, nasogastric tube or urinary catheter insertion	ABC	ABC	ABC	BC	AⒷ	ABC	BⒸ	A	ABⒸ	AⒷ

(continued)

Table 2 (continued)

Risk of exposure	Types of contacts and exposure	Relevant Procedures	Personal Protective Equipment									
			Hand Hygiene	Scrubs	Surgical caps	Surgical masks	N95 masks	Gloves	Disposable gowns	Hazmat suit	Face shields/Eye goggles	Plastic disposable overshoes
	Aerosol-generating upper respiratory tract procedure	Endotracheal intubation, tracheostomy, airway suctioning	ABC	ABC	ABC	C	AB	ABC	BⒸ	A	ABⒸ	AⒷ

Note 1. A, B C: recommended personal protective equipment based on different clinical procedures, while, Ⓐ, Ⓑ, Ⓒare optional; 2. As goggles and face shield provide similar eye protection, HCW may choose to wear one of them. Wearing both simultaneously may reduce clarity of visual field and increase difficulties during procedures and risk of sharp injuries. 3. Use of suction aspirators is recommended during irrigation procedures (including wound irrigation, oral irrigation) to reduce splashes

2.6 Healthcare Facilities Area Division and Management

2.6.1 According to WST-512-2016 Environmental and Surface Cleaning, Disinfection Guidelines [17], the oral and maxillofacial surgery wards and operating theatre can be categorized into 3 areas based of the risk of infection, and the cleaning and disinfection practice for different areas are shown in Table 3.

2.6.1.1 Low risk areas: facilities not accessible by patients, including doctors and nurses' lounges.

Table 3 The cleaning and disinfection practice for different areas

Risks of infection	Methods	Frequency (Per day)	Agents/ Disinfectants
Low risk areas	Use water for cleaning	1–2 times	Water
Moderate risk areas	1. Clean floors with chlorine-containing disinfectants, contact time of approximately 30 min is recommended 2. Contact time of approximately 10 to 30 min is recommended for surfaces disinfection followed by cleaning with water	1–2 times	500 mg/L chlorine-containing disinfectants
High risk areas	1. Clean floors with chlorine-containing disinfectants, contact time of approximately 30 min is recommended 2. Contact time of approximately 10 to 30 min is recommended for surfaces disinfection followed by cleaning with water 3. Thorough cleaning and disinfection are required after each clinical procedure, the subsequent clinical or surgical procedures can only be carried out after terminal cleaning and disinfection of the operating theatre	>2 times	500 mg/L chlorine-containing disinfectants

Note All contaminated (by body fluids, blood, body waste or secretions) areas or surfaces are to be promptly cleaned and disinfected. If it is contaminated by large amount ($\geq$10 mL) of blood or body fluids, absorbent materials can be used to remove the contaminants prior to disinfection

2.6.1.2 Moderate risk areas: areas accessible by patients, mainly the normal wards and doctors' office.

2.6.1.3 High risk areas: infected or contaminated areas or isolation areas for highly susceptible individuals, including operating theatres, intensive care units (ICU)/post-anesthesia care units (PACU), isolation rooms.

Terminal cleaning and disinfection should be performed in high-risk areas in case of admission of suspected or confirmed COVID-19 cases: Spray with 3% sodium hypochlorite solution → contact time of approximately 30 min → regular cleaning and disinfection with 1000 mg/L chlorine-containing compounds → repeat spraying with 3% sodium hypochlorite solution → contact time of approximately 30 min → allow ventilation.

2.6.1 Waste Disinfection and Management

2.6.2.1 In critically ill patients who has not completed COVID-19 screening, the waste disinfection and management are as followed:

I. Healthcare and domestic waste management [28]: Use double layered biohazard bags and disinfection before they are tied.
II. Used instruments or equipment: Use double layered biohazard bags and label accordingly before transporting to designated sterilization unit. Soak instruments or equipment with 1000 mg/L chlorine-containing compounds for 30 min, followed by regular cleaning, disinfection and sterilization. Choice of sterilization for heat-resistant instruments is autoclaves, while chemical disinfection or low-temperature sterilization techniques can be used for sterilization of heat-sensitive instruments [24].
III. Management of hospital linens [24]: Single use and disposable sheets are recommended and will be sent for incineration. If the linens are not heavily soiled, it can be placed in clearly labelled water-soluble bags and soaked in 500 mg/L chlorine-containing compounds for 30 min, followed by regular washing (Guide for Infection Prevention and Control Techniques during COVID-19 2020c).

2.6.2.2 The waste disinfection and management of patients who have completed COVID-19 screening will be carried out according to Clinical Guidelines of Infection Control in Hospital (WST-510–2016) [18].

2.7 Management of Patients' Follow-Up and Review Visits

Follow-up: Patients' education via texts or visual aids using audio, video during the hospital admission is important to reinforce postoperative instructions and precautions. Healthcare workers can utilize internet to contact patients and provide professional and personalized postoperative instructions following discharge.

Review: All patients are required to attend regular reviews postoperatively, patients are encouraged to perform routine investigations at nearest local hospital, prior to discussing the results with attending doctors through telephone, video calls or telehealth services, thus reducing the crowds and risk of cross infection.

2.8 Case Discussion

2.8.1 Inpatient

A 46-year-old lady who works as bus ticket collector. She was allegedly involved in a motor vehicle accident on 14th of February 2020 and sustained right zygomatic arch fracture. She was categorized into the group of "Subacute patients" and the routine screening and risk assessment for COVID-19 were performed and revealed no recent epidemiologic history or contacts with the infected areas for COVID-19. Chest CT scan, blood investigations and vital signs were within normal limits. She was then admitted to ward for further management.

After close monitoring for 3 days in the ward, open reduction and internal fixation (ORIF) of right zygomatic arch fracture was performed on 18th of February 2020. Her vital signs remained stable post-operatively. At post-operative day 4, she complained of chills and rigors, accompanied by body aches, with intermittent coughs. However, there were no signs and symptoms of nasal congestion, sore throat, or dyspnea. Upon examination, the body temperature was 37.4 °C and elevated to 38.6 °C after 1 h, there was no improvement despite administration of oral non-steroidal anti-inflammatory drugs (NSAIDs).

Her body temperature maintained below 37.0 °C on the next morning but she started to present with signs and symptoms of upper respiratory tract infection such as cough, congested and runny nose, sore throat, except dyspnea. There were no significant abnormalities reported from the urgent chest CT scan. Her full blood count revealed white cell count of 3.3×10^9/L and percentage of lymphocytes of 17.5%. The possibility of viral infection cannot be ruled out following consultation with the respiratory medicine team. Screening for Influenza A and B viral infection was performed and reported negative results. Crisis preparedness and response team for COVID-19 was activated and the case was reported to the regional CDC. Regional designated hospital for COVID-19 was then contacted immediately for patient transfer and SARS-CoV 2 test. The patient was transferred according to the standard transfer protocols, and terminal cleaning and disinfection were performed to all contact surfaces and hospital facilities. Simultaneously, the screening for healthcare providers with close contacts with the patient was done under the guidance by CDC. A total of 52 healthcare workers appeared to have had close contacts with the patient. They were placed in isolation for close surveillance and body temperature monitoring. Compulsory isolation was terminated as the two laboratory tests for SARS-CoV 2 and clinical presentation were negative.

Analysis of the case: The case took place in February 2020, where COVID-19 testing was yet to be available nationwide, but only available at COVID-19 designated hospitals. The patient was categorized as 'Subacute patients' and admission protocols was strictly adhered, even before COVID-19 testing was performed. Although there was no recent history of contacts with the infected areas for COVID-19 upon screening prior to admission, attention should be drawn to her occupation as a bus ticket collector. Thus, close monitoring for 3 days following admission was required prior to moderate to high-risk surgical procedure was performed. She presented with flu-like symptoms with fever at post-operative day 4. Although the body temperature returns to normal following medical treatment and tepid sponging, the symptoms of upper respiratory tract infection worsen on the coming morning.

Viral infection cannot be ruled out in view of her blood investigation results despite negative findings in the chest CT scan. Further investigations were carried out to exclude the possibilities of Influenza A and B. Based on the CDC guidance, the patient fulfilled the criteria for COVID-19 screening and was transferred to regional designated COVID-19 hospital as suspected case for further investigations. The above mentioned was the algorithm of patient admission during COVID-19 outbreak and it was proved to be practical and feasible.

2.8.2 Oral and Maxillofacial Surgery (OMFS) Attachment Student

One imported COVID-19 case was reported at Jinan city on 23rd February 2021, in which the patient's RT-PCR and SARS-CoV 2 specific antibody tests were negative during quarantine period. The patient was confirmed as COVID-19 positive 2 days after leaving the quarantine center. Contact tracing showed history of traveling from Taizhou to Jinan via high-speed train (G882).

On 24th February 2021, the OMFS student, named XX, who was attached to postgraduate's outpatient clinic received call from regional CDC, and was informed that she was categorized as close contact, as she was in the same cabin of the high-speed train with the confirmed case. She was then required to self-quarantine at home. Crisis preparedness and response team was activated, and the postgraduate's outpatient clinic was closed for sanitization and disinfection, and the subsequent clinical duties were suspended. Contact tracing confirmed 10 individuals had close contacts with XX, and they were transferred to designated quarantine center with negative pressure ambulance for quarantine. During the quarantine period, the RT-PCR test for XX and other close contacts individuals were negative, and the quarantine was lifted on 15th of March 2021.

Case analysis: This close contact occurred during the journey to Beijing following Chinese New Year holidays. Due to the uncertainties in imported COVID-19 cases and crowds were unavoidable during festive seasons, thus the immediate and prompt response is especially important. As cabin of high-speed train is considered as enclosed space, therefore once there is a confirmed COVID-19 case, the other passengers will be listed as close contacts. Hospital crisis preparedness and response team took prompt and appropriate actions in managing the individuals and other healthcare workers after receiving the notice from CDC. This ensures the safe and smooth operation of the subsequent teaching activities at postgraduate outpatient clinic, in which the emergency protocol management was proved to be feasible.

References

1. Chang, T., Hong, G., Paganelli, C., et al.: Innovation of dental education during COVID-19 pandemic. J. Dent. Sci. **16**(1), 15–20 (2021)
2. Chavarría-Bolaños, D., Gómez-Fernández, A., Dittel-Jiménez, C. et al.: E-learning in dental schools in the times of COVID-19: a review and analysis of an educational resource in times of the COVID-19 pandemic. Odovtos-Int. J. Dent. Sci. 207–224 (2020)
3. Fujita, Y., Shiono, Y., Maki, K.: Knowledge of emergency management of avulsed tooth among Japanese dental students. BMC Oral Health **14**, 34 (2014)
4. Giugliano, T., Chikunov, I., Zhivago, P. et al.: A digital method of teaching artificial teeth arrangement. J. Dent. Educ. 1– 3 (2020). https://doi.org/10.1002/jdd.12325
5. Iyer, P., Aziz, K., Ojcius, D.M.: Impact of COVID-19 on dental education in the United States. J. Dent. Educ. **84**(6), 718–722 (2020)
6. Machado, R., Bonan, P., Perez, D. et al.: COVID-19 pandemic and the impact on dental education: discussing current and future perspectives. Braz. Oral Res. 34 (2020)
7. Mahrous, A., Alammari, R., Elgreatly, A.: Implementing virtual OSCE using an open-source online interactive 3D library. J. Dent. Educ. 1–3 (2020). https://doi.org/10.1002/jdd.12449
8. Mladenovic, R., Bukumiric, Z., Mladenovic, K.: Influence of a dedicated mobile application on studying traumatic dental injuries during student isolation. J. Dent. Educ. 1– 3 (2020). https://doi.org/10.1002/jdd.12250
9. Mladenovic, R., Bukumiric, Z., Mladenovic, K.: Practice of local anesthesia applications in 3D environment during the COVID-19 pandemic. J. Dent. Educ. 1– 3 (2020). https://doi.org/10.1002/jdd.12410
10. Mladenovic, R., Dakovic, D., Pereira, L., et al.: Effect of augmented reality simulation on administration of local anaesthesia in paediatric patients. Eur. J. Dent. Educ. **24**(3), 507–512 (2020)
11. Mladenovic, R., Davidovic, B., Tusek, I. et al.: The effect of a mobile application for learning about traumatic dental injuries during the COVID-19 pandemic. Srpski arhiv za celokupno lekarstvo 7–7 (2021). https://doi.org/10.2298/SARH201110007M
12. Mladenovic, R., Djordjevic, F.: Effectiveness of virtual reality as a distraction on anxiety and pain during impacted mandibular third molar surgery under local Anesthesia. J. Stomatol. Oral Maxillofac. Surg. (2021). https://doi.org/10.1016/j.jormas.2021.03.009
13. Mladenovic, R., Mladenovic, K., Milanovic, P. et al: Augmented reality technology as a method of distance learning for local anesthesia training. J. Dent. Educ. 1–3 (2021). https://doi.org/10.1002/jdd.12581
14. Mladenovic, R., Pereira, L., Djordjevic, F., et al.: The use of mobile-aided learning in education of local anesthesia for the inferior alveolar nerve block. Vojnosanit. Pregl. **77**(8), 839–843 (2020)
15. Mladenovic, R., Pereira, L., Mladenovic, K., et al.: Effectiveness of augmented reality mobile simulator in teaching local anesthesia of inferior alveolar nerve block. J. Dent. Educ. **83**(4), 423–428 (2019)
16. Movchun, V., Lushkov, R., Pronkin, N.: Prediction of individual learning style in e-learning systems: opportunities and limitations in dental education. Educ. Inf. Technol. (2020). https://doi.org/10.1007/s10639-020-10372-4

17. National Health and Family Planning Commission of People's Republic of China: Regulation for cleaning and disinfection management of environmental surface in healthcare (WST-512-2016) (2016)
18. National Health and Family Planning Commission of People's Republic of China: Regulation for hospital infection management norms in wards (WST-510-2016) (2016)
19. Santos, G.N., Leite, A.F., Figueiredo, P.T., et al.: Effectiveness of E-learning in oral radiology education: a systematic review. J. Dent. Educ. **80**, 1126–1139 (2016)
20. Shuang, L., Kai, X., Jinqiu, L.: Research on the relationship between the COVID-19 and the diagnosis and treatment of otolaryngology [J]. Chin. Otorhinolaryngol. Head Neck Surg. **27**(06), 307–310 (2020)
21. Suebnukarn, S., Haddawy, P., Rhienmora, P., et al.: Augmented kinematic feedback from haptic virtual reality for dental skill acquisition. J. Dent. Educ. **74**(12), 1357–1366 (2010)
22. Sukotjo, C., Schreiber, S., Chun Yuan, J.C., et al.: Faculty perceptions of virtual reality as an alternative solution for preclinical skills during the pandemic. J. Dent. Educ. (2020). https://doi.org/10.1002/jdd.12499
23. The General Office of the National Health Commission: Notice for the Guidelines for infection prevention and control during perioperative period of New Coronavirus Pneumonia (Trial Edition) (NSC Medical Letter No. 162) (2020-03-17) (2020)
24. The General Office of the National Health Commission: Notice on Issuing the Technical Guidelines for the Prevention and Control of the New Coronavirus Pneumonia Infection in Medical Institutions (Second Edition) (NSC Medical Letter No. 169) (2020-04-06) (2020)
25. The General Office of the National Health Commission: Notice on the New Coronavirus Pneumonia treatment plan (Trial Eighth Edition) (NSC Medical Letter No. 680) (2020-08-19) (2020)
26. The General Office of the National Health Commission: Notice on the New Coronavirus Pneumonia treatment plan (Trial revised Eighth Edition) (NSC Medical Letter No. 191) (2021-04-14) (2020)
27. The General Office of the National Health Commission: Notice on the issuance of technical guidelines for the protection of medical personnel during the New Coronavirus Pneumonia epidemic (Trial Edition) (NSC Medical Letter No. 155) (2020-02-21) (2020)
28. The General Office of the National Health Commission: The General Office of the National Health Commission. Notice on the New Coronavirus Pneumonia treatment plan (Trial third Edition) (NSC Medical Letter No. 80) (2020-01-28) (2020)
29. Yue, Y., Soh, H.Y., Zhi, G.C., et al.: Experience of diagnosis and management of patients in oral maxillofacial surgery during the prevention and control period of the new coronavirus pneumonia. Chin. J. Dent. Res. **23**(1), 57–62 (2020)

Location Intelligence and Community Resilience in Pandemic Situations

Digitizing Pandemic Response Operations: The Experiences from a Small Island Nation

M. Aboobakuru, S. Moosa, S. K. Usman, and H. Shafeeu

Abstract Timely information on population, their locations and health information, is central to a pandemic response. In the Maldives, a geographically dispersed archipelago, information technology is a necessity for the pandemic response. This chapter examines the information and data flow in relation to the business processes of the pandemic response, the technologies adopted and how these were used. Observations, interviews, data systems analysis and business process mapping were used for this study. The findings underscore the critical role the digitized pandemic response operations system "Outbreak", played for timely response and decision making for effective pandemic control. The experiences in establishing a verifiable identification system, motivation and confidence of the technology users, connecting health care providers and intersectoral institutions are discussed. The sheer shortage of human resources for the notify-test-trace-isolate-care strategy, internet connectivity across the country, policy commitment, technology friendly populace and urgency were the critical driving forces. Since the core pandemic response processes and information needs are nearly universal across countries, the concepts and system described here provide a framework for other small island countries and resource poor settings to improve pandemic operations. The Outbreak system has the potential to be developed with capabilities for connecting with institutions across international borders, for future pandemics preparedness and responding to endemic disease outbreaks.

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1 Introduction

The COVID-19 pandemic was a crisis beyond health for many countries, particularly the low income and small island countries. This is due to the pre-pandemic challenges in the health systems and development including technological developments. In the Maldives, the pandemic posed challenges for delivery of health care and other services to small, geographically dispersed islands in the archipelago, with travel and movement across and between islands restricted. The pandemic halted all established service and product delivery channels in many ways. This forced all the sectors to identify alternative pathways and adopt digital platforms. The sectors and people adapted and evolved to a more techno-friendly response.

This chapter demonstrates the utility of digitizing the pandemic response management for effective control of the pandemic, in a resource poor and logistically challenging environment. It examines the information and data flow in relation to the business processes of the pandemic response, the technologies adopted and used in these processes and how these were used in the operations and decision making in the Maldives. Observations, interviews, data systems analysis, business process mapping and validation with focus group discussions as well as the experiences of the system users were used for this study and literature are analyzed for drawing conclusions.

The Maldives is an archipelago of over 1000 islands dispersed across the Indian Ocean with very small populations per island, with a total population estimated at 568,362 in 2021 [13]. The geographic dispersion of the islands and challenges of travel by boats, had led to investments in increasing digital connectivity in a number of small island countries such as the Maldives. Maldives is currently ahead of most South Asian countries in terms of digital connectivity. According to [17], 63% of the population uses internet and 57% of the population has unique mobile subscriptions (Fig. 1). However, as compared with other South Asian countries, the monthly prices of a mobile broadband basket (1.5 GB of monthly data allowance) is higher in the Maldives and people with access to 3G/4G is lower [17].

These statistics indicate that the digital transformation is taking place in the country at a rapid pace and sets the environment to further accelerated adoption of digital technologies. Smartphone (mobile phone) ownership is prevalent across the country, with nearly all households owning at least one smartphone [17]. As [5] noted, although there is a relationship between gross national income (GNI) and ownership of technology devices, the same is not observed for technology adoption. The affordability, internet speed, access to digital support and the level of digital skills of the population are factors that can determine that these devices are actually used to access the Internet [5]. With over one third of the Maldivian population residing in Male', the capital of Maldives, there is an obvious digital divide, based

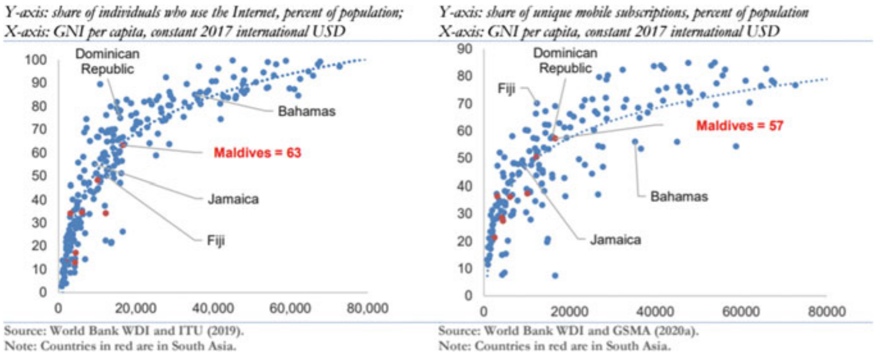

Fig. 1 Access to internet and mobile phones (*Source* [17])

on location, education and income. In this sense, Male' has more access to devices, twice the download speed of internet compared to atolls (World Bank, 2021. Despite these caveats, the country provided a favourable context to adopt digital options in the pandemic response and discounts were provided by the providers to mitigate some of the negative impacts of the pandemic [2, 17] (Fig. 2).

In this context, at the onset of the pandemic most of the businesses tapped into the digital literate community and made their platforms online. They started online shops and delivery across the Maldives and public utility companies switched to digital bills and accepted payments via internet. Some schools that have already handed out tablets and established means to deliver the curriculum via online platforms started teaching online and health services started online consultations [12]. The government information systems and workforce, however, were not ready for a digital response. The digital infrastructure, platforms and ecosystems that are capable of providing information and communication technology solutions were limited in the public sector and is evidenced by the lower e-government development index for Maldives compared to regional countries such as Sri Lanka [18]. Existing information systems were neither efficient, nor consistent [10]. The workforce was not

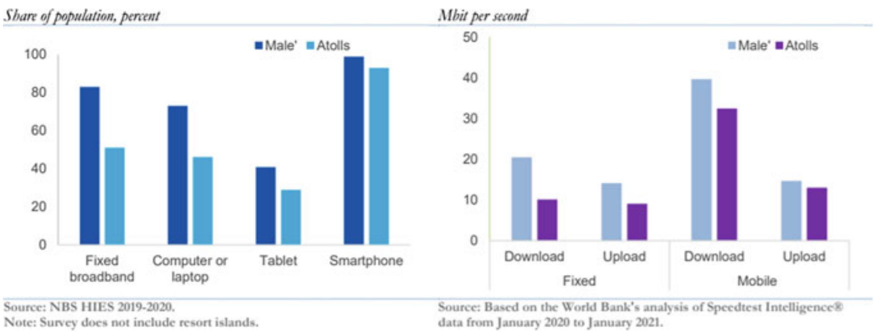

Fig. 2 Access to digital devices and Internet speed in the Maldives ([*Source* 17])

confident with the security of the systems and processes ensuring confidentiality of information, which made the systems operate in silos. Hence, the social services and public administration lagged behind and picked up the momentum much slowly.

The following sections examine how the pandemic response adopted digital technology in its emergency operations to provide timely interventions and services to the people and keep the people informed.

2 Business Process and Information/Data Flow

The COVID-19 pandemic response in the Maldives like many other countries adopted the notify-test-trace-isolate-care approach. Operationalizing this strategy required data on population characteristics, their residential localities and households, contact information, domestic and international travel history, health and social situation data. In any country, this information is collected and produced by different institutions distributed across the government, business institutions and the public [15]. As with many middle-income countries (MICs), most information systems are neither digitized nor complete in the Maldives. Even the health information systems are developed only for the institutional needs and do not capture important elements for a public health response [19]. Furthermore, like in many other countries, existing electronic information systems lack interoperability hampering timely exchange of information needed in a public health emergency [9].

Information on the population residing on different islands and their locations were extremely critical in the pandemic response as they are the clients of the response. Maldives has a national identity registration system for its citizens that enable verification of identity of the person and their permanent addresses. However, it lacks information on their current location. This was the limiting factor in planning and reaching the at-risk population during the response as no service in country necessitated registering temporary address. Even the utility services are registered to household owners rather than the residents—residents frequently seen to be moving their place of stay for various reasons A variety of information sources were available that could provide a solution to this, and attempts were made to tap into the information systems of telecom providers, national health insurance records and even hospital records. Despite this, none of the systems could verify the contact details and current location of the individual. While these challenges existed for citizens, information on foreign migrants' resident locations proved to be nearly impossible as a data source is not available. Even for travelers, information was accessed from the tourist establishments, as the only single source, immigration records, include only the initial check-in places and hence has no way of tracking movements within the country. The solution was to verify from the individual once contact has been made. This situation required whole of government and society approach, working together to exchange up-to-date information and a platform that could draw on these siloed information sources.

In the Maldives' response, the strategy of notify-test-trace-isolate-care was based on the epidemic investigation processes. Table 1 presents the data requisites in conducting the epidemiological investigation that forms the basis of the strategy.

In any information system solutions, it takes time to connect and interface existing databases and sources of information. However, the pandemic situation did not allow this and hence a new information system "Outbreak" customized to the business process of the COVID-19 operations was crafted in a short span of time and rolled out and tested and debugged as the operations continued. A prerequisite for the system development was a clear understanding of the business processes and associated

Table 1 Data requisites at each stage of the business process of the operations

Process	Information needs	Sources	Technologies
Identification	Identity*—locals, foreign workers, travelers	Department of national registration (locals); Immigration department (travelers and foreign migrant workers)	Databases—local or on network (cloud)
	Current residence location*	Person; Employers (civil service)	Mobile phone, Databases
	Contact number*	Person; telecom providers	Mobile phone, Databases
	Clinical symptoms	Person; Border health; Health facility	Mobile phones; Spreadsheets; email;
Testing	Identity of authorized personnel (licensed)	Health facilities and laboratories; Allied Health Professionals' Council; Emergency operations centre (EOC)	Databases
	Unique identifier for the sample	System generated number; bar codes	Mobile phone; barcode generator; barcode reader
	Designated labs	Health ministry	Database; Spreadsheet
	Test specific details (brand, type, kits, controls	Designated laboratories;	Polymerase chain reaction (PCR); lateral flow; rapid test
Tracing	Travel history	Immigration; border health	Databases; social media
	Movement details	Person; phone	Location apps;
	Workplace	Person; Employers	Attendance databases
	Household	Person; Family member; landlord	Phone; social media
	Recreational and sport	Person; colleagues; sports associations	Social media

(continued)

Table 1 (continued)

Process	Information needs	Sources	Technologies
	Shops and Food establishments	Person; colleagues; Economic ministry; City council	Databases
	Tourist establishments	Person; Tourism ministry	Databases; digital registries
Isolation	Designated facilities	Health ministry	
	Identity of authorized careers	Health facilities and laboratories; Professional Council (medical, nursing, allied health); EOC	Databases
	Diagnostic data (radiology/laboratory)	Health facilities; designated facilities	Patient information system; medical technologies
	Clinical status	Health facilities; designated facilities	Patient information system; medical technologies
Care	Underlying health conditions	Person; Health facilities; health care cover providers	Databases; medical records
	Underlying functional disability	Person; Health facilities; health care cover providers; Social Protection Agency;	Databases; medical records; social protection benefit records
	Identity of vulnerable persons	Person; Family member; Social Protection Agency; Social services ministry	Databases; phone contact
	Carer details (identity and contact number)	Person; Family member; Department of national registration (locals);	Databases; phone contact
Other: essential movements	COVID-19 case information	EOC	Database; mobile app
	Reasons for movement	Person; health facility; Island councils	Emails; phone; mobile app
	Assessment of destination residence	health facility; Island councils; police service	Emails; phone; mobile app

* Required in all processes

information needs of each process. Figure 3 shows the core business process in the Maldives COVID-19 emergency operations centre (EOC). Other business processes, particularly those related to movement of people between islands for essential and emergency purposes during periods of curfew and domestic travel restrictions that also required connectivity with the Outbreak system. The process for these activities goes beyond EOC to the island administrations and was also considered as an integral part of the Outbreak system in its development.

Other countries have also adopted information systems for the pandemic using frameworks based on the epidemic stages [3]. Ye and colleagues [19] note that each stage of the epidemic requires integrated application of various information sources technologies and the importance of developing the information and technology solutions based on these. Similarly, in the Maldives, the framework for conceptualizing the digital operations was based on the information needs (Table 1 and the business process (Fig. 3) of the EOC.

3 Concept and Schema of the Outbreak System

A comprehensive, event-driven system to digitize COVID-19 response and relief efforts for the Maldives, Outbreak provides person centric automation tools for the pandemic operations; surveillance, contact tracing, quarantine management, COVID-19 testing, call centre and emergency response and giving special attention to the vulnerable.

The system triggers COVID-19 surveillance protocols from the point of symptoms reporting, initiates COVID-19 tests and contact tracing mechanisms. The system facilitates escalated events and tasks with regard to positive cases and those that need special care (Fig. 4).

Connecting all laboratory facilities with polymerase chain reaction (PCR) capability across the country and enabling Rapid Response Teams for sample collection using the specialized *Sampler* application ensures smooth testing for more than a 3000 PCR tests daily. The Sampler application is optimized to making COVID-19 test sample collection, movement, and results entry seamless. Automated scheduled result notification and result based triggers is a feature embedded into Outbreak.

The self-reporting portal *Haalubelun* extends ability for every person to raise emergencies and to request for quarantine movement. The *Haalubelun* portal is used to submit the health status of those under monitoring, reach emergency response should an incident occur, reserve online consultations, and check the COVID-19 test results. *Haalubelun* facilitates persons and families who want to move to another area to request for home quarantine. The systems have automated scheduling mechanisms to trigger request for release sampling where applicable and consequent automated quarantine release.

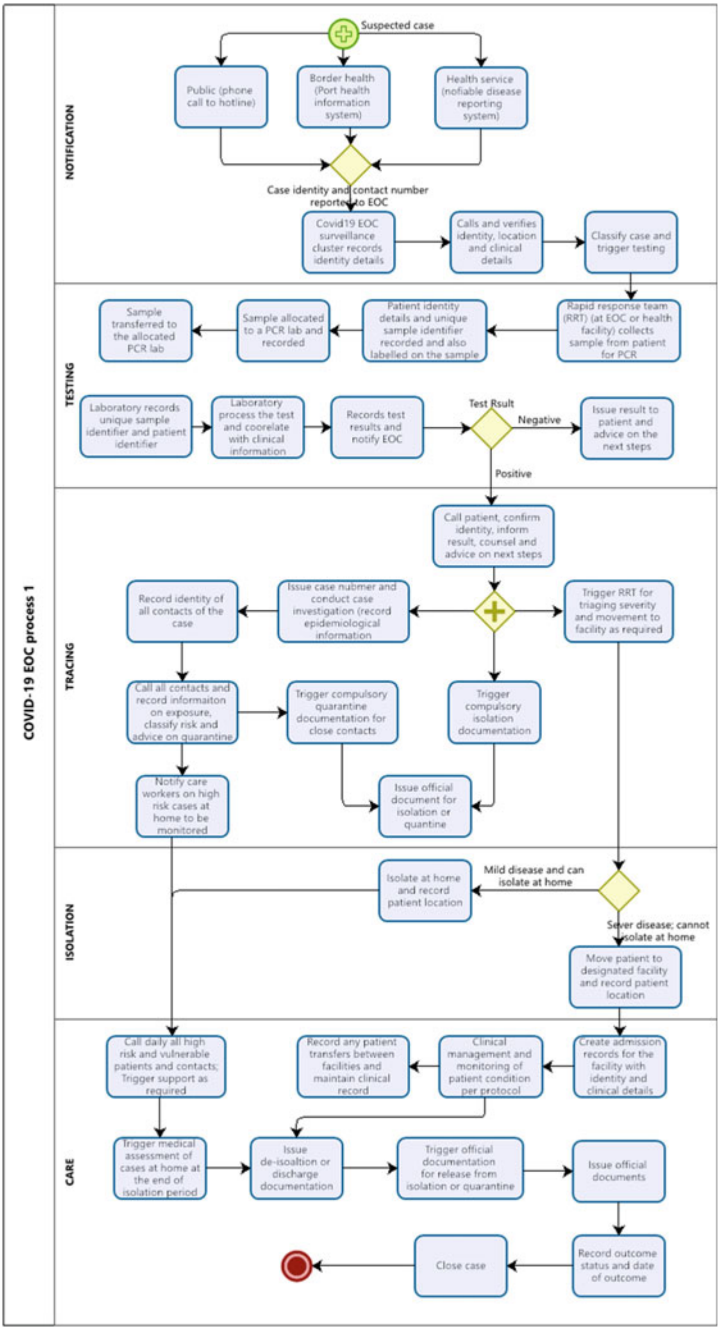

Fig. 3 Business process at COVID-19 EOC, using notify-test-trace-isolate-care approach. *Source* authors compilation

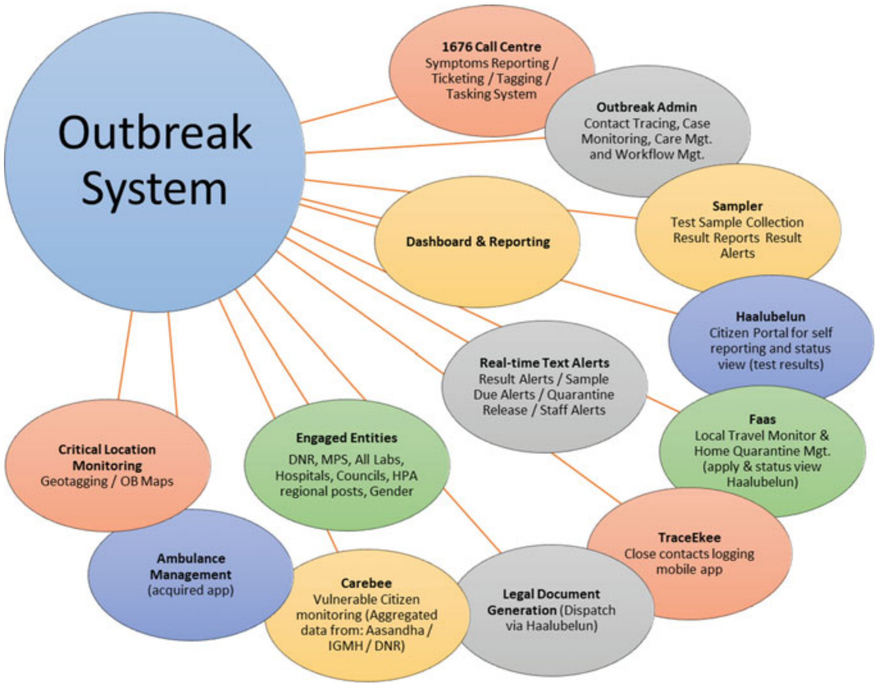

Fig. 4 The components of the online COVID-19 Response Systems, Outbreak. *Source* authors compilation

The system also provides the *Faas* interface for councils and hospitality sector to process quarantine services. *Faas* allows island councils to approve requests for families to get quarantined in their island and affirm when they arrive. *Faas* also provides for quarantine process in industrial and hospitality islands and facilities.

The systems are interconnected via APIs and data systems and sources authorized identification data directly from relevant authorities for data validation. All systems operate in tandem relying on one another to facilitate the holistic total toolkit for the operations.

Business Intelligence and data analytics tools provide aggregation and data analysis capability with features to generate on the tap queries, dashboards and graphs from live data for better visibility of trends and status, facilitating data driven decision making. Location geotags are used to provide heatmaps of the spread of infection. In addition, searchable node graphs are provided for surveillance to facilitate tracing of contacts and epidemiological analysis (Fig. 5).

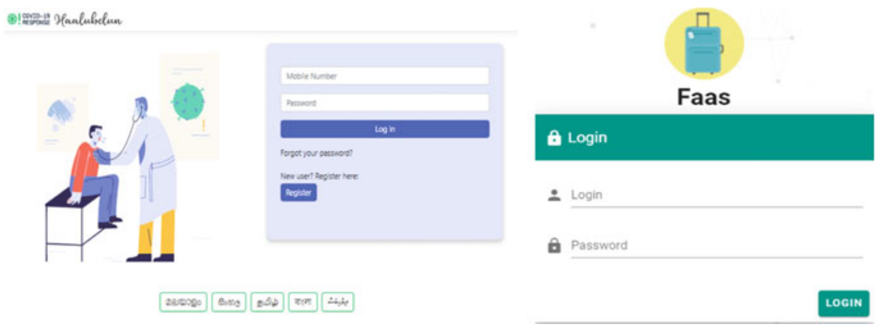

Fig. 5 Login view of Haalubelun and Faas poral. *Source* Health Protection Agency, Maldives

4 Utility of the Digitized Operations System

The system met a number of objectives in terms of providing timely alerts and metrices of the operations in terms of operational targets and its outputs. Operational targets for the EOC were set at, to achieve over 80% completion of tasks for almost all clusters within 48 h. Embedded alerts to the relevant persons in charge of each process was critical for timely response. For instance, one operational target is to complete contact tracing and isolation of 80% of the case within 48 h at the designated locations. As per the business process, Outbreak sent out alerts to the mobile phone of operations head in real time as laboratory enters the test results in the system. This triggers tickets to the tracing and isolation within seconds. The system has enabled Maldives to maintain their response performance target well above the limit, throughout 2020.

Another critical feature of the system that improved performance of the pandemic response is the mechanism that links Outbreak to the call centre and providing them with access to generate multiple tickets to response operations clusters. This was particularly important in responding to community reported suspected cases, triaged online, advising and collecting samples to the issuance of the results. Realtime analytics of operational tasks facilitated timely action. Key metrices provided by the analytics were categorized into pending, started, ongoing, on-hold, cancelled, completed closed. The incident manager had a key role to play in monitoring these key metrices and carryout the necessary follow-up actions with the respective clusters (Fig. 6).

Critical to the response operations were the add-ons to the Outbreak. *Haalubelun* and *Faas* portal though not directly related to health response, they were critical for facilitating safe movement of people for and to provide essential services across the country. These applications allowed for community engagement of the response and expected to facilitate safe practices. Furthermore, the applications allowed for smoother intersectoral collaboration between local councils and tourism sector.

The features of the system and analytics were beneficial beyond the operational actions—it facilitated epidemiological analysis and monitor the epidemic. Features

Fig. 6 Examples of analytics metrices used to monitor performance of the operations. *Source* Health Protection Agency, Maldives

such as trend charts, node and heat maps were useful for the epidemiological analysis and forecasting the epidemic spread.

Key to the epidemiological analysis were the dashboard and health map and the capability of the system to query different questions required for epidemiological analysis. One example of this was the alert of possible UK variant (now classified as alpha variant) of the SARS-CoV2 in the country, using the S-Gene Target Failure from the test results entered into Outbreak. In a scenario that did not allow such analysis, the public health professionals had to send samples to an international lab for genome sequencing of the virus, that was expected to take several months. In the current pandemic continuous data analytics and forecasting are critical for informing policy and public health decisions [1]. The capability of the Outbreak allowed real-time analytics that facilitated timely decisions on appropriate public health interventions.

Research into the evolving pandemic situation was also supported by Outbreak. For instance, in the seroprevalence study of COVID-19 in Male' area, Outbreak was used to generate the sampling frame, contact information of selected participants and issuing results of the serological tests through the messaging function in the Outbreak. This reduced the duration of the research and provided timely evidence to produce epidemic forecasts for decision making. The Outbreak has the potential to support further epidemiological research on COVID-19 in the country that should be more widely used by the researchers.

5 Lessons and Experiences

In the digitization of the pandemic response, intersectoral collaboration was key to its success. Although the country is regarded as a high middle-income country, resources are scarce and digital services are just emerging in business use. Current work processes in public institutions rely little on electronic, digital platforms and applications. The existing information systems are designed for the purpose of the institution and the owners of these systems are extremely protective of their systems. In this backdrop, lobbying for high level policy and commitment was required to initiate dialogue and process of collaboration. However, high level commitment alone was not adequate to implement such collaboration and data sharing as has been reported in other countries [14]. Other countries' experiences observed that frictions in terms of transaction costs are common in such joint processes, and notes that these emerge due to inefficient institutional capabilities and technical skills and poor communication rather than inadequate infrastructure [4]. Fears and misconceptions about data integrity and security were key concerns and addressing the fears of the managerial and operational staff was necessary to move forward. It was important to demonstrate common principles stakeholders can identify with regard to data integrity, security and confidentiality of the data and develop a level of trust between the parties [20]. Multiple consultations at different level of the organizations (middle management and technical operations) were necessary to develop effective collaboration with other stakeholders. Whole of government approach and commitment to work on a linked platform enabled overcoming the pre-existing frictions while increasing access to the services for the public at a time of limited physical interaction.

Motivation of the users was equally important for successful digitization of the pandemic operations in the country. As with any information system or digitized process users' motivation became critical for effective implementation the Outbreak system. Demonstration of the utility of the system in improving performance of the operations were key to motivation of the users. Developing confidence in the system by training the responders on the Outbreak system was found critical to effective deployment [20]. Sensitization and awareness sessions were staged to allow for buy-in from incident managers and cluster heads at the outset. This was quite challenging as the EOC was responding to emergency and finding time and attention of the key personnel was a limiting factor for quick decision on digitizing the operations. At the second stage, training of the responders proved to be more challenging than expected, not because of a higher skill level required for the digitized process, but due to the large number of volunteers involved that were always changing. This was overcome by providing more intensive training to the permanent staff of the health system and public institutions involved in the response, so that they could act as master trainers in their respective process in the operations. This strategy proved useful with the prolonged pandemic operations by creating skill and capacities within the health system to absorb the technology that may be useful in future institutionalization of the system [11]. A challenge however is the system support that require the institutions to take control of the system, as this requires a workforce with higher skills who has a good understanding of the system algorithms and the work process [6]. This needs to be considered by the health policy makers to ensure the benefit of the system is used in other national disease control programmes in the country.

The pandemic operations required exchange of personal information between the EOC clusters, health care facility, local councils and police services and digital exchange have shown to improve efficiency of the response in other settings as well [19]. Maintaining confidentiality of information was a core principle adopted throughout the digitization process and use of Outbreak in the operations, particularly in the absence of adequate legal frameworks for privacy protection in the use of information technology in the country. It was observed, that public quite freely divulge personal information among their informal networks, perhaps influenced by the close-knit community in the islands of Maldives. However, confidence in the government institutions is low in the country as was observed in the low uptake of the local version of the *TraceTogether* application. Even though data governance was centralized at EOC, the evolving nature of the operations with high reliance on volunteers meant that the users frequently changed. This required monthly checks on user access and their current roles in the operations and adjusting or removing the user access. Data confidentiality becomes particularly important in relation to maintaining privacy of personal information when using a digital system as it has the potential to create social problems, not only for the clients, but also for the workers that blur their professional personal boundaries. Pan and Zhang [15]. In the Maldives, one of the main concerns that further enhanced the need for the confidentiality of information was the stigma and discrimination the cases and contacts faced during the pandemic.

Furthermore, as the operations require action in other sectors for citizen services in the context of movement restrictions, the plugins to the Outbreak, *Haalubelun* and *Faas* applications were extremely useful catering to the public's domestic essential travel needs. It allowed intersectoral collaboration and enhanced coordination between local council, police services and the tourism sector, building team spirit among the response partners working towards a common goal serving for the public safety. The tourism sector used the *Faas* portal to ensure the tourism industry workers movement to and from tourist resorts complied with the public health measures, including quarantine for the designated period followed by testing prior to starting work. The connections made with the tourism sector was critical not only for essential services but opening tourism safely in the country.

The digitized response using Outbreak and plugins, particularly *Haalubelun* paved way to establish connection and engagement with the public and opened avenues for societal functioning to some extent. The technology friendly populace is one factor that made this digital service effective. Nevertheless, some segments of the population, particularly elderly and unskilled foreign migrant workers were at a disadvantage. Some of this was overcome with the support from members of the family and employers taking the initiative to support these segments. The digital divide is a concern across any society, yet the benefits of digitization in service provision far outweigh the disadvantages, particularly in pandemic situations [5, 16]. The experience of Maldives pandemic operations has been mostly positive and has demonstrated due diligence needs to be maintained to cater for those needing support in using digitized services. The lessons from digitization of the pandemic operations will be valuable in institutionalizing this technology solution in the public health system for management of other disease outbreaks.

6 Opportunities and Recommendations

The digitization experience has provided several opportunities to further refine the Outbreak system and institutionalized it in the health system. Its established connections with different health care institutions hold promise to widen the scope of the Outbreak as the national disease surveillance system. This is particularly relevant for the control of endemic communicable disease outbreaks when information and analytics is needed for public health decisions and measures. The possibility of expanding the scope of Outbreak system to have the capabilities to cater to multiple disease outbreaks needs to be explored, as there are subtle differences in the business process to that of the pandemic in endemic disease outbreaks. Furthermore, digitized surveillance systems at country level will open the door to embark on contributing more effectively to global epidemiological surveillance and epidemic alerts [8].

The COVID-19 vaccination module is still in its infancy and needs to be further integrated into the Outbreak to allow for required analytics for decision making. Furthermore, the vaccination involves further processes such as monitoring of adverse events following immunization which require more detailed clinical and diagnostic reporting. The value to the system can be enhanced with capabilities to provide information on these parameters. This is particularly relevant for future domestic and international travel as countries and airlines are contemplating introduction of proof of vaccination [7].

The collaboration established with island councils, police services and the tourism sector hold promise for continued partnership for public health. These collaborations however need to be nurtured to develop an environment of trust and confidence in data governance. Continued work towards interoperable and shared platforms is likely to pave way towards digitizing a range of public services. Development partners have noted the potential for the government to progress towards e-government [17].

To reap further benefits of digitization a number of structural investments and legislative changes needs to be made. First, it is recommended that necessary changes are made to existing data systems to update resident information on current address and contact details. This is a priority given the central role current resident location of people need to be verified for emergency response. Secondly, legislative framework needs to be put in place for data governance and confidentiality in digital developments, management of digital information system and digital administrative processes of the government. The third recommendation is to develop institution capacity, particularly skills of the workers to maintain and produce data analytics from the information systems. Finally establish a community support mechanism to assist those segments of the population with low digital literacy to be able to engage with institutions on an online platform. Fourth, but not the least, is to explore possible cross border collaboration with public health institutions in other countries, particularly in relation to the health status of travelers. With countries enforcing requirements for test results and vaccination records, developing compatible pandemic response systems with application programming interphase between national systems that allow for paperless verification of health risks for travelers, with appropriate cyber security, will be a milestone in global health security.

The study of the experiences of the digitization of the pandemic response in this small island country has allowed to produce a framework based on the response strategy notify-test-trace-isolate-care, linking epidemic investigation stages with its information needs. This framework can be adopted and similar digitized response system can be developed in different country contexts and in national endemic disease control. Critical to its success is due consideration of the business processes and motivation of the users and partners involved in the pandemic response.

References

1. Ågerfalk, P.J., Conboy, K., Myers, M.D.: Information systems in the age of pandemics: COVID-19 and beyond. Eur. J. Inf. Syst. **29**(3), 203–207 (2020). https://doi.org/10.1080/0960085X.2020.1771968
2. Ahmed, S.: Dhiraagu introduces free data package for students, teachers. The Edition (2021). Accessed from https://edition.mv/news/15850
3. Asadzadeh, A., Pakkhoo, S., Saeidabad, M.M., Khezri, H., Ferdousi, R.: Information technology in emergency management of COVID-19 outbreak. Inform. Med. Unlocked 100475 (2020)
4. Bonina, C., Koskinen, K., Eaton, B., Gawer, A.: Digital platforms for development: foundations and research agenda. Inf. Syst. J. 1–34 (2021). https://doi.org/10.1111/isj.12326
5. Fong, M.W.L.: Digital divide: The case of developing countries. Issues Informing Sci. Inf. Technol. **6**(2), 471–478 (2009)
6. Harteis, C.: Digitalisation of work. work-based learning as a pathway to competence-based education. In: Bahl, A., Dietzen, A. (Eds.), Work-based Learning as a Pathway to Competence-based Education: A UNEVOC Network Contribution, pp 85–97 . Federal Institute for Vocational Education and Training (2019)
7. International Air Transport Association [IATA]: IATA Travel Pass Initiative. IATA (2021). Accessed from https://www.iata.org/en/programs/passenger/travel-pass/
8. Kostkova, P., Saigí-Rubió, F., Eguia, H., Borbolla, D., Verschuuren, M., Hamilton, C., Novillo-Ortiz, D.: Data and digital solutions to support surveillance strategies in the context of the COVID-19 pandemic. Front. Digit. Health **3**, 89 (2021)
9. Krausz, M., Westenberg, J.N., Vigo, D., Spence, R.T., Ramsey, D.: Emergency response to COVID-19 in Canada: platform development and implementation for eHealth in crisis management. JMIR Public Health Surveill. **6**(2), e18995 (2020)
10. Maldives Financial Review: The digital future is 'loading...'. Maldives Financial Review (2021). https://mfr.mv/public-sector/the-digital-future-is-loading
11. Mansell, R.: Digital opportunities and the missing link for developing countries. Oxf. Rev. Econ. Policy **17**(2), 282–295 (2001)
12. Moosa, S., Ibrahim, A., Usman, S.K.: *S*ocial sector experience during the COVID-19 pandemic's lockdown in the Maldives. Male', Maldives: The Maldives National University (2021)
13. National Burau of Statistics: Maldives in Figures April 2021: Male', Maldives: National Bureau of Statistics (2021)
14. Niedzwiecka, M., Pan, Y.C.: An exploratory study into employee attitudes towards digitalisation of library services in higher education. In: Proceedings of the 22nd UK Academy for Information Systems Annual Conference (UKAIS). April 2017; Oxford, UK (2017)

15. Pan, S.L., Zhang, S.: From fighting COVID-19 pandemic to tackling sustainable development goals: an opportunity for responsible information systems research. Int. J. Inf. Manag. **55**, 102196 (2020)
16. Selwyn, N., Facer, K.: Beyond the digital divide. Opening Education Reports. Bristol: Futurelab (2007). Accessed 24 Oct 2007
17. The World Bank: Maldives development update April 2021: a digital dawn. The International Bank for Reconstruction and Development/ The World Bank, New York (2021)
18. United Nations Department of Economic and Social Affairs [UNDESA]: E-government Development Index (2021). https://publicadministration.un.org/egovkb/en-us/Data/Country-Information/id/104-Maldives.
19. Ye, Q., Zhou, J., Wu, H.: Using information technology to manage the COVID-19 pandemic: development of a technical framework based on practical experience in China. JMIR Med. Inform. **8**(6), e19515 (2020)
20. Yusoff, W.Y., Abas, Z., Muhd Yusuf, D.H.: Electronic government procurement adoption behavior amongst Malaysian SMEs. Int. Bus. Res. **4**(1), 100–111 (2011)

Resilience to COVID-19 Pandemic

Sanaz Moghim, Voznyuk Alexander, Mudita Sinha, Rybalka Valentyn, and Leena N. Fukey

Abstract Coronavirus disease 2019 (COVID-19) is a global issue that has been affecting all countries differently. The number of confirmed cases, recoveries, and deaths in each country can reflect the appropriateness of the response and reaction of the governments and people. To better illustrate the preparedness and capacity of the countries to cope with this crisis, a health resilience score (HRS) is defined. The HRS is an indicator that integrates the normalized number of death and recovery rates. This score can indicate a relative performance of the countries in managing COVID-19. To increase community health resilience, the integration of physical and mental health care is crucial. Uncertainties and lack of control cause stress that affects mental health and thus immune system. This chapter discusses causes and effects of stress and ways to prevent and manage it. In addition, the application of information and communications technology (ICT) in education as one of the sectors that aggravate stress during pandemic and lockdown is explained. Enhancing resilience not only in the health system but also in sectors including environment, livestock agriculture, and academics during pandemic can reduce the risk of damages now and in the future. An important message of this pandemic is that the integrity of the world and ecosystem is essential for a sustainable health system.

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Keywords Crisis resilience · Mental health · Stress · Information and communications technology (ICT) · Education · Global integrity

1 Introduction

COVID-19 is one of the deadly contagious diseases, which is considered as a global disaster [18]. To develop the ability of the communities to overcome this risk, community health resilience needs to be improved. The health resilience is the capacity of the communities to adapt to changes and recover from crisis [28]. To compare the performance of the countries in risk and disaster management, different studies defined varied resilience indicators or scores like Social Progress Index, SPI [12] and Human Development Index, HDI [22]. For instance, based on Resilience Index 2021, global economic resilience decreased by 18% in 2020 due to COVID-19 pandemic [9]. To reduce vulnerability to coronavirus crisis, an integrated mental and physical health care should be included in developing resilience strategies [28]. The COVID-19 pandemic includes many challenges, uncertainties, bad feelings that increase stress and thus decrease resilience (Centers for Disease Control and Prevention, CDC).

All diseases are followed by stress. Uncertainties, lack of control and information are the main causes of stress that directly affects physical and psychological health [5]. The mechanism of psychological defense has been most fully studied in the context of the theory of cognitive dissonance or cognitive distribution [8], which shows that we do not process information properly, but distort it so that it satisfies our previously acquired ideas [2]. Thoughts and feelings related to unpleasant associations, memories, and experiences weaken the thymus. Pleasant thoughts and associations strengthen the thymus and the “Life Energy”, which is defined as “Homing thoughts” [7]. If you need a lift, strengthen your thymus with a “homing thought” – think of something uplifting [25].

The theory and practice of avoiding stressful situations proposed by [21] highlighted the benefits of normal stress and the harm of negative types (especially distress and frustration) to the health. One of the main causes of stress during the pandemic and lockdown is school closures. Due to outbreak and fast spread of COVID-19, governments around the globe are compelled to close the functioning of the school and colleges temporarily to restrict the spread of the disease [24]. The lockdown across nations has affected the entire population of student largely. This has forced the governments across the globe to introduce new methods of technology enabled teaching to reduce the knowledge and learning gap among students (Robin et al. 2020).

Student population is greatly affected across the globe. In 1946, United Nations established a specialized agency named United Nations Educational, Scientific and Cultural Organization (UNESCO) with the main goal of encouraging peace and security through international collaboration. One of the several projects handled by UNESCO is education and they are taking great initiatives to keep the learning process active among students in this pandemic situation. It has been estimated by

UNESCO that more than 60% of the world student's population is affected due to the closures of school in nationwide lockdowns, which has influenced millions of students. UNESCO declared that due to closure of schools around 32 crores of students are affected in India, where the high rate of infection and death occurred [23]. It is quite indicative from the images (Figs. 1 and 2) taken from the UNSESCO

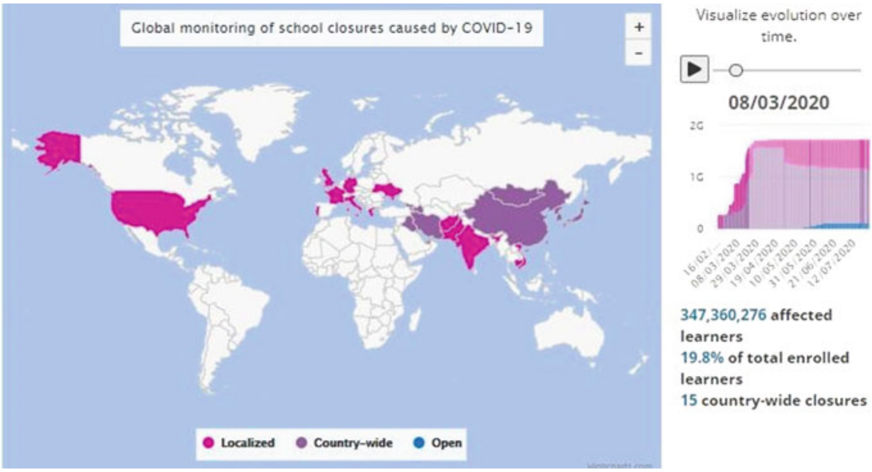

Fig. 1 The number of learners enrolled at pre-primary, primary, lower-secondary, and upper-secondary levels of education [ISCED levels 0 to 3], as well as at tertiary education levels [ISCED levels 5 to 8]; Figure from UNESCO Education Response [23]

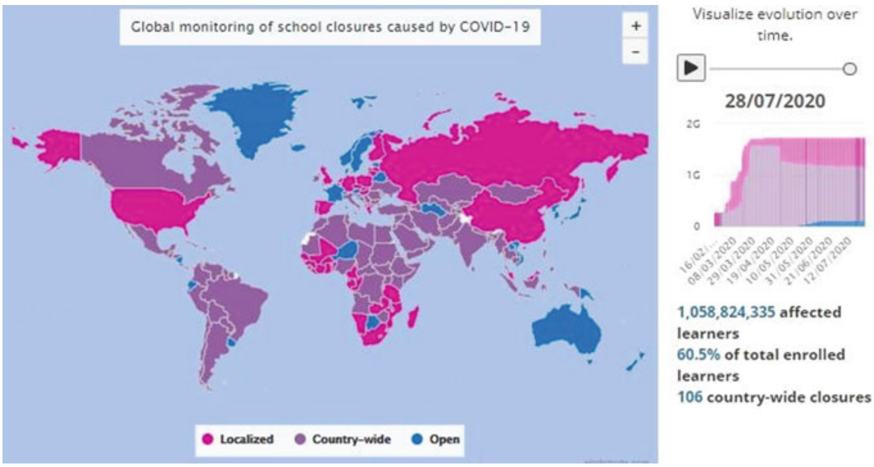

Fig. 2 The number of learners enrolled at pre-primary, primary, lower-secondary, and upper-secondary levels of education [ISCED levels 0 to 3], as well as at tertiary education levels [ISCED levels 5 to 8]. Figure from UNESCO Education Response [23]

webpage that how drastically this pandemic has shadowed the closures of schools worldwide form 15 country-wide closures in March 2020 to 106 country-wide closures in July 2020 and the statistic is increasing exponentially with every passing day.

This chapter defines a health resilience score to compare the performance of the countries in handling the COVID-19 outbreak. In addition, causes and effects of stress on mental health and immune system during pandemic are addressed. Techniques and strategies that reduce stress and increase resilience are explained. For instance, the benefits, challenges, and impact of information and communications technology (ICT) on education are discussed.

2 Health Resilience Score

Resilience is the main factor of success in disaster management. Although resilience defines differently in varied organizations (e.g. DFID,[1] UNISDR,[2] IPCC[3]), the main concept as "the ability of the system to properly resist and recover from negative impacts of disaster" is similar. Resilience as the process of coping with COVID-19 (as a crisis) can be defined based on death and recovery rate. Related data including confirmed cases, deaths, and population are obtained from European CDC (www.ecdc.europa.eu). The data used in this study are from the day when the 5th deaths are confirmed for each country till 15th June 2020 [15], in which the coronavirus outbreak started (first wave). The death and recovery rates due to COVID-19, that are the total number of confirmed deaths and recoveries per population, are normalized between -1 and 1. The normalized death ($X_d^{'}$) and recovery ($X_r^{'}$) rates are integrated to form the health resilience score (HRS) as

$$\mathrm{HRS} = X_r^{'} - X_d^{'} \tag{1}$$

Indeed, $X_d^{'}$ and $X_r^{'}$ have negative and positive loading in this resilience score, respectively. Large absolute values of the normalized recovery rate (towards + 1) and normalized death rate (towards -1) enhance resilience score. The CDF (cumulative density function) of the HRS [F(HRS)] can show a relative levels of scores in countries [11]. Percentiles of the CDF including 2.50%, 8.54%, 26.99%, and 66.98% are used to classify countries into five levels of health resilience. Countries with the probability of health resilience score [F(HRS)] smaller than 2.50%, between 2.50% and 8.54%, between 8.54% and 26.99%, between 26.99% and 66.98%, and larger than 66.98% have very low, low, moderate, high, and very high score, respectively. Figure 3 shows classification of the countries based on these levels of health resilience.

[1] Department for International Development.

[2] United Nations International Strategy for Disaster Reduction.

[3] International Panel on Climate Change.

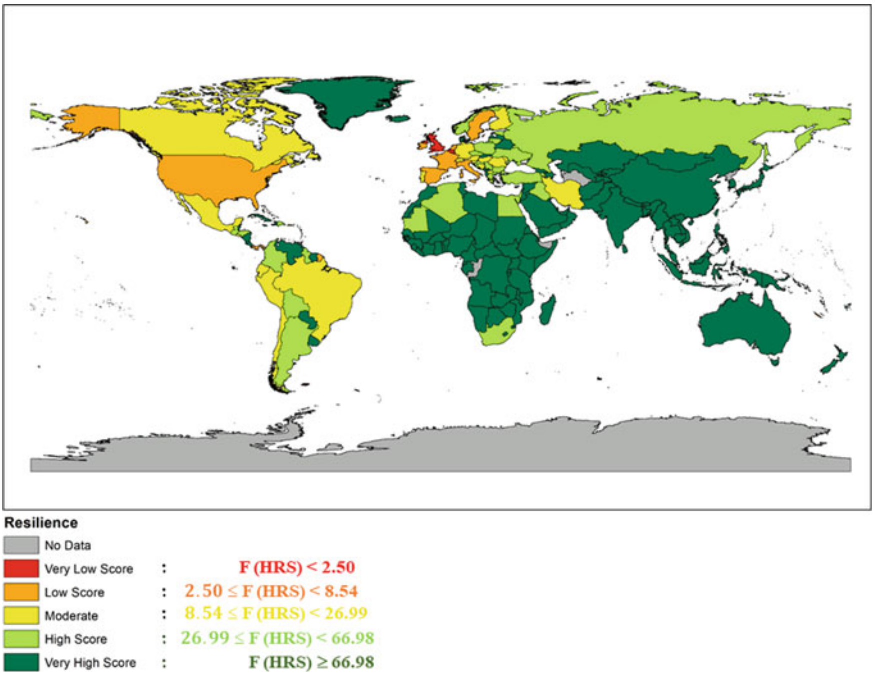

Fig. 3 Health Resilience Score (HRS) of the countries

Figure 3 can indicate a relative grade of countries on dealing with COVID-19. Most countries in Asia and Africa have high resilience score, which can refer to a small number of deaths and a large number of recoveries relative to their population. Andorra, Belgium, Luxembourg, San Marino, and United Kingdom have the lowest score, which can reveal a large number of deaths and a small number of recoveries in those countries. In north and center of Europe, different resilience scores in nearby countries (neighbors) can be observed. For instance, Scandinavian countries, Germany and neighbors (e.g. Denmark, Netherlands, Belgium, Austria, and Poland) are in different health resilience groups.

The developed health resilience score based on the probability distribution can consider some uncertainties that are related to the data. HRS as a proper indicator allows for a fair comparison of the COVID-19 situation among countries. This index can consider different factors that are vital in health resilience by integrating both numbers of deaths and recoveries. Different levels of HRS in nearby countries can highlight the role of policy of the countries in dealing with COVID-19 crisis. In addition, the average age of people and eating/dietary habits in countries can affect the risk of getting sick and dying. Medical conditions, healthcare access/quality, health insurance, and related costs also influence the number of deaths and recoveries. More detailed information about age, career, and underlying medical condition of the infected and dead people in each country can help government and public to make the best possible decisions to cope with the disease. For instance, restrictions, certain plans, and support for specific groups, that are at higher risk (e.g. based on age or job), can reduce not only the pandemic growth rate but also limitations for other groups, which is important for economic growth and mental health of the countries.

The most resilient countries integrate adaptation and mitigation strategies that lead to an increase in the number of recoveries and a decrease in the number of corona-infected cases. An integrated adaptation and mitigation framework developed by "high health resilience" countries is an invaluable source of information for all countries now and in the future that more pandemics are expected due to population, economic, and technological growth and environmental ignorance. Results confirm that governments that noticed the first cases quickly and took fast and emergency actions in response to outbreak are more successful in handling COVID-19. To reduce possible risks, these countries should continue to monitor the situation closely and make sure that people are following the rules and specific policies. On the other hand, delayed response and improper policies in "low health resilience" countries resulted in unavoidable outcomes and risks. Although results are shown for the first wave of COVID-19, the global distribution of this score can be different in next waves. This difference can indicate varied responses and policies of the countries to deal with this pandemic. Countries that learned lessons from the first wave, applied their own and other countries' experiences, and predicted next waves and possible issues like mutation and COVID-19 variants, are better prepared to overcome this pandemic. Resilient countries strengthen community and social health system to overcome negative effects of COVID-19. To increase health resilience during pandemic and crisis both physical and mental health should be improved.

3 Connection Between Mental and Physical Health

Mental health care plays vital role in dealing with the new situation during the coronavirus pandemic. Mental and physical health affects immune system. Any issue in either mental or physical health influences immune system and thus causes or exacerbates existed problems. Although coronavirus directly affects physical health like respiratory system, it can influence mental health through fear of getting infected, stress, grief, and pain of loss. These factors directly influence normal functioning of the immune system and responses. Indeed, the physical and mental health feedbacks are in a loop, in which initial responses to either physical or mental health problems lead to positive feedbacks. In other words, positive feedbacks between physical and mental health issues weaken the immune system. This continuous loop leads to severe consequences and symptoms. An analysis of scientific literature on various aspects of health concludes that "health as a psychophysiological entity most fully characterizes the state of integrity of the human body, thus ensuring the functional completeness and diversity of this organism (Voznyuk 2018)". Integrity at the psychophysiological level suggests that all organs and systems of human body are in functional unity. This integrity of the human being is manifested in the fact that any negative stimulus of external environment is met by the organism in the form of the stress, leading to various diseases [17]. Indeed, stress is one of the main factors that exacerbates negative impacts in a connected loop of physical and mental health. The stress, the nonspecific response of the body as a whole to any stimulus, is accompanied by a set of nonspecific reactions that are common to all diseases without exception. Thus, a narrow set of reasons or some universal factor lies at the root of any disease including COVID-19, which leads to the weakening of the organism's vitality/immunity. This section focuses on stress as one the main triggers that affects mental and physical health.

3.1 Effects of Stress

Stress can energize a person, restore their interest to life, and also cause exhaustion and illness. Indeed, stress that is a response of the body to uncertain, dangerous, and detrimental situations is not always bad. This natural reaction is vital to protect us from possible threats and dangers. People deal with stress differently and different bodies have varied vulnerabilities to the stress. For instance, during the pandemic, stress can make people take COVID-19 risks more seriously. Furthermore, it can be a trigger of proper tasks and actions, which are important in mitigation and adaptation to the risks and new conditions. Although human bodies manage levels of stress differently, everyone can deal with a certain dose of stress. Prolonged chronic stress contains emotional (e.g. depression, loss of control), behavioral (e.g. not eating or eating/drinking too much), and physical symptoms (e.g. headache, insomnia, continuous colds, infections). The severity of the symptoms depends on levels of stress and the strength of the immune response. If a person cannot manage stress properly, the emotional (stressful) reaction can lead to "closure" of the body both literally and figuratively. The blood vessels contract and the blood pressure increases, which causes deteriorating the trophic functions of the tissues and organs. All ensuing physiological consequences trigger consequent diseases whose treatment should consist an elimination of the causes but not the symptoms. Note that some physical symptoms of mental disorders and COVID-19 are similar that can lead to confusion, high anxiety, and stress. Mental disorders weaken immune system and influence physical illness like heart diseases, which is the main cause of the global death.

Our long-term studies have led to discovering five types of stress that correspond to five types of temperament. The fifth type was revealed by Tsukanov, a Ukrainian scientist, who proposed to call this type an equilibrium type, since it is located between choleroids and sanguinoids, on the one hand, and melancholoids and phlegmatoids, on the other [20]. Thus, a psychotherapy who works with people to overcome stress should take into account their temperament. Speaking about the types of temperament, one can pay attention to such preferred diseases and the symptoms stemming from the conditions of person's psychodynamic incongruence as:

(a) possible cholecystitis, hepatitis in choleroids;
(b) myocardial infarction in sanguinoids (about half of their total number);
(c) lung diseases and the problems with kidneys in the representatives of the equilibrium type;
(d) angina pectoris and hypertension in melancholoids;
(e) probable gastrointestinal disorders and diseases, even stomach ulcers in phlegmatoids.

In the course of our work, it turned out that during the psychological consultations on different psychological and behavioral problems, it is possible to give advice that actually reduces painful manifestations or even leads to the removal of clients' diseases. It should be especially noted that the representatives of equilibrium type of temperament are characterized by pulmonary and renal diseases as preferred diseases. There are 4% of such representatives in the entire population. In the light of statistical data on coronavirus disease in a pandemic, they can be considered as a high-risk group. In our opinion, this group that can form the core of 10–15% of the population are open to the coronavirus threat, which is consistent with the results of [20].

The disease occurs when human cannot adequately respond to external stimuli because of their own psychological and worldview inadequacy, which leads to forming a lot of negative psychological sets and social attitudes that in their turn generate different diseases. Negative perception and attitude to reality leads to weakening energy tonus. This was proved by John Diamond, the founder of Life-Energy Analysis (formerly Behavioral Kinesiology), a system based on Applied Kinesiology, who developed what he termed "Life-Energy Analysis" in the 1970s [7].

3.2 Causes of Stress

Selye discovered that the greatest and single contributor to physiological mechanism of stress is human negative thoughts and feelings, which is why the annihilation of these symptoms lies in the positive emotions such as love, gratitude, and goodwill [25]. Negative emotions are the state of stress that, according to the information theory of emotions of Simonov, stem from the lack of information regarding the process of satisfying current needs [19]. Based on the information theory of emotions, we can believe that emotion, as the lack of information about the outside world is an expression of situational uncertainty as well as the fundamental uncertainty in today and tomorrow.

Everyone should have enough valid information about COVID-19 for efficient collaborative efforts. Lack of data and information about this disease and required actions by countries affects our analysis of the situation. In addition, limited testing and different policies of the governments to announce an accurate number of cases (deaths and recoveries) can mislead our understanding. The number of the confirmed cases can be underestimated since no symptom is observed in many infected people. In addition, symptoms vary in infected groups with different ages, which makes

COVID-19 recognition harder. Detection of mortality due to COVID-19 in many countries is still a challenge. Different scientific results and news about coronavirus increase uncertainties. The complex condition that includes high uncertainties can increase stress and anxiety in people. The COVID-19 pandemic has been initiating feeling of mental discomfort that leads to an alteration of the attitudes, beliefs, or behaviors. Contradiction between ideas and information leads to doubts and loss of adequate perception. In addition, experiences including success and failure in previous illnesses and pandemics influence our perception and understanding. Although the history and memory of everyone is important to generate stress, uncertainties and concerns for the future can trigger or exacerbate stress and anxiety.

4 Mental Health Resilience

The psycho-energy-behavioral factor of human life has a decisive impact on human health. Similar to virus, energy, moods, and thoughts of the people are exchangeable and contagious, which can spread globally. During personal contacts, the disturbances in mental balance, destructive emotional reactions, and negative values/attitudes can be transmitted from one human being to another worldwide. Thus, a positive mood and attitude towards the world is a factor to increase the resilience and vitality of a person and strengthen their immunity with all the social and biomedical consequences. During the pandemic when people face contradiction between ideas and lack of information, those who are able to think in a paradoxically ambiguous way can eliminate this ambivalence. They overcome the cognitive ambivalence of opposing events/cognitions by combining the opposites into an intermediate cognition being a neutral paradoxical essence. Indeed, "creative" paradoxical metamorphic thinking can unite the opposites and reconcile warring parties. This act as the ability to connect opposing entities and operate them is a leading factor in human development in ontogenesis and phylogenesis [13]. This ability is particularly crucial during the global pandemic of new diseases like COVID-19, when people are facing uncertainties and many different findings. Members in community and families should act like a chain to build a resilient system. For instance, parents should control their stress without transferring it to the others. Stress and anxiety are contagious like virus and can quickly spread. Although stress of the pandemic affects kids, parents play an important role to cause and exacerbate stress in younger age groups. Coronavirus may have lower risks for kids (younger age) while stress can affect their immune system and lead to mental disorders. Indeed, the consequences of the pandemic significantly influence their lives. It is hard for kids to integrate opposites and uncertainties of the situation and be "creative". We need to ease conditions for kids to make them feel safe and secure.

There are many contradictions and uncertainties about COVID-19 from the beginning (e.g. the origin of the virus, factors of transmission, symptoms, care/safety tips, treatment, medicines). A "creative" person, who acts as an open system that perceives the world with full confidence and combines its polar aspects, can better associate the concept with opposite meanings. Creative people can maintain the state of uncertainty for a long time due to their ability to self-reflection and their capacity to use several ideas, concepts, and theories being opposite to each other. Thus, creative people can explore such relationships and relate them [16]. Creativity as a process of combining contradictory and conflicting thoughts/perspective can create new integrities (meanings), which is the main feature of the evolutionary mechanism. This mechanism that is essential to manage and relieve stress and anxiety particularly during an uncertain situation like COVID-19 pandemic can increase mental health resilience.

Distress is one of the factors that reduces the level of functioning the immune system, thus we need to apply proper anti-distress methods. For instance, the psychological training directed at creating person's ability to recover from intense chronic stress and anxiety compensates for depletion of the nervous system. In this aspect, the autogenous training that aims at improving the respiratory system, eliminating infections, and strengthening the immune system and health is beneficial. To relax and relieve stress, we need skills and abilities. There are techniques and strategies to reduce stress as follows:

- recalling the experience of working with similar problems in the past; the experience of successes and failures can enable us to cope with distress;
- checking our attitude to the problems and changing thoughts/perspective; development of an attitude toward positivity and effectiveness of actions helps to manage stress. Kind attitude and being careful increases the ability to relax and achieve a state of peace;
- avoiding bad and invalid news and information;
- focusing on improving physical strength and body resistance at different types of stress (e.g. good sleep and exact "tuning" of the body through exercise);
- organizing proper human nutrition.

Concerns and lack of control over new conditions trigger stress. To boost resilience for better stress relief it is important to know and predict challenges and changes during the pandemic. One of the main concerns of the parents during the pandemic and lockdown is their relationship and communication with the kids. In addition, education/learning is one of main issues and causes of the stress for both kids and parents during the pandemic that needs to be handled properly. Indeed, governments are responsible to build required infrastructure to deal with these issues during the pandemic. Ignorance and lack of attention and proper actions leads to stress that can be followed by dissatisfaction, disappointment, sadness, regret, anxiety, and other mental disorders. Issues in education and mental health are important not only during the pandemic but also after that.

5 Lifeline of Education System During COVID-19 Pandemic

Education as one the main rights for everyone is a big concern during the pandemic. Educational institutes are centres for communal activity and people interaction, which is especially important for overall development of students. The regular academic session halted due to the lockdown. During the closure of institutes, students lose the social development. UNESCO is trying to support different countries especially more affected and destitute countries to catalyze the continuity of learning progression via distant learning, which is the most suitable solution for the current scenario [23]. It provides convenient, readily available and reasonable access to lessons. The usage of information and communications technology (ICT) in education across the world has become widespread. The continuation of the existing education system has been possible only because of ICT, which needs to be properly established by governments and educational institutions. The term ICT can refer to data, correspondence, and innovation while data innovation and correspondence innovation cannot stand freely thus it represents innovation. Nevertheless, this meaning and significance of the term ICT is unbalanced and appears to be inadequate. Besides, it might propose data, correspondence, and innovation. Another perspective of ICT can refer to.

1. Data (or information) in paper or electronic configuration;
2. Correspondence face to face or electronically (electronic correspondence), recorded as a hard copy or voice media communications and broadcasting;
3. Data or Information Technology (IT)—including programming, equipment and hardware;
4. Correspondence Technology—including conventions, programming and equipment.

There are different methods of utilization of ICT in training, for example, computer supported, computer based, Internet based or software based as follows:

- PC supported: with the presentation of ICT in instruction, homeroom learning is one trait that makes learning experiential and trial to understudies. Understudies can tune in to the teacher, get obvious signs through PowerPoint pictures, freebees or whiteboard records and partake effectively.
- PC based: It confers PC information in understudies and empowers them to acquire many data put away in the framework. It likewise encourages the understudies to process information and use it properly.
- Internet based: Internet apparatuses like email, informal communities, newsgroups and video transmission have been used more than ever. With the assistance of long-range interpersonal communication destinations and messages, the students can cooperate and share data. Web based learning and separation adapting additionally work through web. The understudies can learn on the web and can likewise converse with specialists on the web. Moreover, understudies from anywhere can obtain notes, instructional exercises, and tasks. The web gives

significant data in messages, sounds, recordings, and illustrations, which can be received by each person.

Similarly, there are different methods of utilization of ICT in instruction, for example, computer helped, computer based, Internet based, and software based. Different structures can be applied for control of the universities/colleges/schools, which are changing to a more of blended learning of synchronous and asynchronous mode with the support of specially designed teaching-learning software for improved learning management systems of educational institutes. Although application of ICT certainly has positive impacts, it poses many challenges. Primarily it has cost and it needs installation and availability of computers, projector, smart board, scanner, television etc. These devices are expensive, and many students and teachers cannot afford it. In addition, the cost of buying licensed software is extremely high. Moreover, Internet, which plays a significant role in transmission of knowledge in ICT, may hinder the learning for those who do not have stable Internet connection. Despite of these challenges, the responsibility of creating educational activity system robust, dynamic and output-oriented rests with all the stakeholders of education sector especially teachers, administrators, universities, and government. Thus, governments and decision makers should ease the use of the ICT and different empowerment technologies like Internet, smart objects, and sensors that can be effectively utilized for education during the pandemic. Indeed, education is one of the main sectors that needs to be resilient during the COVID-19 pandemic. Resilience not only in education but also in all sectors that are affected by the pandemic is crucial for efficient recovery and reduction of lose and damages.

6 Proper Actions and Strategies During Pandemic for Developing Resilience

To combat COVID-19, it is necessary to combine individual and institutional strategies and tactics of conscious psychological counteraction to the threat of coronavirus infection and disease. Corresponding to new results, findings, and statistics, frequent systematic development and update of management plans is required. A person, who appears not as a defenseless passive object of the negative impact from a pandemic, but as a subject actively acting according to a certain program, can successfully counter the pandemic threat. It is important for everyone to become a full-fledged subject of self-protective actions, promptly using scientific data on the nature of the pandemic that appears online. People may need to consider different types of communication and lifestyle. For instance, countries need to be placed on lockdown during the pandemic, which should be fully managed and protected by the governments. In a lockdown situation, establishing constructive interaction in the family between adults, parents, and children is needed. Elderly people, as the most vulnerable category of the adult population with weak immune system and functional insufficiency, deserve special attention. On the other hand, old people are enriched in a unique life experience and the ability to survive in hard conditions. Therefore, older people should receive special psychological assistance and, at the same time, act as competent experts in overcoming the difficulties associated with the coronavirus pandemic.

To protect others and ourselves from COVID-19 it is important to consider safety rules, advice, and precautions (i.e. wearing masks, keeping away from the crowd, keeping a safe distance, washing hands frequently, and vaccination). An important role of a kind of vaccine against coronavirus disease can be played by some types of psychological defense revealing some internal mechanisms of human life, including the body's immune system. Since there are uncertainties about the vaccines such as vaccination efficacy, immunization coverage, level and duration of immunity, everyone needs to follow the health tips and protocols even after vaccination. If people think logically about a pandemic, disease, and treatment steps, they would be able to consider issues and possibilities in the future that are fundamental in overcoming and managing stress. For instance, someone may get COVID-19 even after vaccination. Although it affects people's perspective, thoughts, hope, and trust, it is important to remember the pros and ratio of infections after COVID-19 vaccination. Global vaccination can boost immune system and decrease the risk of infection, level of severity, virus transmission, mutation, and severe symptoms.

The government strategic plan not only in providing guidelines and vaccines but also in increasing public trust for vaccination and implementation of recommendations during the pandemic is crucial. Although governments and policy makers are playing critical and vital roles in overcoming COVID-19 and decreasing related risks, success of COVID-19 control needs support for plans and decisions. In other words, the role of the people to mitigate or exacerbate hazards should not be ignored. Proper interaction, reasonable communication, and mutual relationship between governments and people can build trust, credibility, confidence, and collaboration. Indeed, not only the governments but also everyone should know their roles and their contribution to COVID-19 hazards and controls.

At the same time, the harmonious homeostatic state should be steadily maintained not only in each body, but also in the course of organism's interaction with other bodies and the environment. For instance, in COVID-19 like many other diseases, the animal-human bond transferred virus and the virus spread between people and thus led to a global pandemic. The human–human transmission can cause virus variants and mutation. This conclusion leads us to the idea about the integrity of the world and corresponds to the phenomenology of health, which is implemented as a phenomenon of integrity. Indeed, the integrity of the sustainable ecosystem and mental/physical health of all people is vital to enhance the resilience of the world in the face of hazards like COVID-19.

7 Concluding Remarks

Resilience is an important indicator of success or failure in coping with hazards and risks. The developed health resilience score (HRS) indicates the relative ability of the countries in recovery and adaptation during COVID-19 pandemic. HRS that is a health-related indicator can illustrate an integrated view of levels of risk and hazard controls in COVID-19. Different policies of the countries in dealing with different types of crisis (e.g. in health, environment, academics, energy, economy, and society) lead to varied levels of success/failure in managing each of those hazards. To resolve the global issues like COVID-19 unity among countries is required. Increased awareness/responsibilities, quick actions, unity/integrity, valid communication, and reliable collaboration play fundamental role to stop disease outbreak. In addition, honesty and clarity in communication between government-people and among leaders is vital to control global hazards of coronavirus before improper actions turn crisis into a disaster. Experiences of all countries including the most and the least successful (resilient) ones at prevention and control of COVID-19 should be documented and publicly available in WHO. Those experiences and lessons are essential to avoid or overcome the next pandemics.

To increase community health resilience both physical and mental health should be improved. Although the physical symptoms of the COVID-19 are apparent, the mental health disorders are not easily noticeable, which needs to be diagnosed properly. Indeed, the mental health issues not only during the pandemic but also after COVID-19 should be considered seriously. Uncertainties and various possibilities, which can be perceived differently, triggers stress that can cause or exacerbate health problems. It is important to consider lateral factors like stress and anxiety disorders that influence immunity particularly during the pandemic. Note that both excess and lack of stress can be hazardous to human health. Indeed, according to some leading experts, up to 90% of all diseases are "stress-dependent", that is, they are associated with stress [1, 6, 10, 17]. Overall, negative person's psychological states arise from stress being an information phenomenon, accompanied by a decrease in body's energy tone and realized in the situations of informational uncertainty, which leads to stressful states and behaviors. The latter is expressed in negative psychosocial reactions of fear, anger, depression, aggression, sadness, and frustration. Conversely, positive emotional states associated with optimism fill our body with energy.

Education, training, and self-development during the pandemic and lockdown is one of the global concerns and causes of stress. One of the resources that can efficiently help to handle these issues is ICT. Although ICT has challenges and difficulties, it is generally beneficial in easing the situation. Indeed, ICT, which may continue to be used even after pandemic, avoided learning lose due to school closure.

To prevent the next pandemics, the whole story of COVID-19 should be reviewed carefully from the origin of the coronavirus to the end of this pandemic. The pandemic has brought extensive changes in society and many of these changes will be long lasting. Outputs and findings of this pandemic should be applied in adaptation and mitigation plans of related sectors like health, environment, food marketing, communications, education, and society. One of the main highlights of this pandemic is to remember how human health depends on a healthy planet and living organisms. Although technological progress can facilitate human lives and productivity, which is required particularly with population growth, it can lead to degrade environment and put living organisms at risk. This global lockdown provides an opportunity to restore ecosystem health and sustainability. For instance, a significant reduction in pollution of air, water, land, and sound is reported globally [3, 29, 30]. Indeed, conservation of ecosystem and natural resources (e.g. animal, plant, water, air, soil) is essential for the food chain. Improper use of ecosystem services threatens human health and lives. The fast outbreak of this pandemic can highlight not only the mutual dependence between ecosystem and human health but also the importance of integrity of the world. The pandemic will not end without global unity of the human and ecosystem, which needs support of health standards and safety policy.

To improve coping ability for new situation during the coronavirus pandemic, resilience in different sectors is important. Resilience as the ability to adapt and recover quickly should be developed in human beings, ecosystem, natural resources (e.g. animal, plant, air, water, land), and their linkages/interconnections. Indeed, resilience level in sectors like health system, environment, and academics is an indicator of incurring damages and overcoming difficulties/hazards, which is a fundamental principle for a sustainable society. Similarly, other measures should be defined to assess the impact of this pandemic on different sectors like mental health, social behavior, environment, and economy that is affected largely. In addition, more studies should assess and monitor connections and linkages between health system and other related sectors and highlight the application of ICT in other fields (e.g. marketing, business, economy) during pandemic.

References

1. Argyle, M. (1987) The psychology of happiness. Methuen & Co. LTD. London & New York, 275 p.
2. Aronson, E. (2004) The social animal. (9 ed.) Worth/Freeman
3. Basu, B., Murphy, E., Molter, A., Basu, A.S., Sannigrahi, S., Belmonte, M., Pilla, F.: Investigating changes in noise pollution due to the COVID-19 lockdown: The case of Dublin, Ireland. Sustain. Cities Soc. **65**, 102597 (2021)
4. CDC, Centers for Disease Control and Prevention. Retrieved from https://www.cdc.gov/mentalhealth/stress-coping/cope-with-stress/index.html
5. Chopra, D., Tanzi, R.E.: Super Genes: Unlock the Astonishing power of your DNA for optimum health and well-being. Harmony, New York (2017)
6. Cousins, N. (1979) Anatomy of Illness: As Perceived by the Patient Cousins. N. Y.: W. W. Norton and Company, 295 p.
7. Diamond, J.M.: Behavioral Kinesiology. How to Activate Your Thymus and Increase Your Life Energy. Harper and Row, N. Y. (1979)
8. Festinger, L.: A theory of cognitive dissonance. Stanford University Press, Stanford, CA (1957)
9. Gillespie, F. (2021) Resilience Index 2021: a strong growth recovery, but less resilient world economy, sigma, Swiss Re Institute

10. Greer, S., Watson, M.: Towards a psychobiological model of cancer: psychological considerations. Soc. Sci. Med. **20**, 773–777 (1985)
11. Moghim, S., Kaveh Garna, R.: Countries' Classification by Environmental Resilience. J. Environ. Manage. **230**, 345–354 (2019)
12. Porter, M. E., Stern, S., Green, M. (2014) Social Progress Index 2014. Social Progress Imperative Washington, DC
13. Poršnev, B. F. (1979) O začiatkoch ľudských dejín Švihran J. Jazykovedný Časopis Veda. vydavateľstvo slovenskej akademie vied. 194–195
14. Robin, A. K. and Gupta, S. (2020) Present Education System in India: A Challenging Priority in the Society. NOLEGEIN-Journal of Operations Research & Management, 1–5
15. Roser, M., Ritchie, H., Ortiz-Ospina, E., and Hasell, J. (2020) "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. Retrieved from. https://ourworldindata.org/coronavirus [Online Resource]
16. Rotenberg, V. S. (1985) Hypnosis and imaginative thinking. Psychological Journal, 6, 23–34 (https://egoland.ru/gipnoz-i-obraznoe-myishlenie)
17. Selye, H.: Stress Without Distress. J. B. Lippincott Co, Philadelphia (1974)
18. Sheek-Hussein, M., Abu-Zidan, F.M., Stip, E.: Disaster management of the psychological impact of the COVID-19 pandemic. Int. J. Emerg. Med. **14**, 19 (2021)
19. Simonov, P.: The motivated brain: a neurophysiological analysis of human behavior. Gordon and Breach Science Publishers, Philadelphia (1991)
20. Tsukanov, B. I. (2000) Time in the Human Psyche. Odessa: Astroprint (https://www.twirpx.com/file/66578/)
21. Tubesing, D. A. (1981) Kicking Your Stress Habits: A Do-It-Yourself Guide for Coping with Stress. Penguin Group (USA) Incorporated
22. UNDP (2016) Human Development Index (HDI). Retrieved from: http://hdr.undp.org/en/content/human-development-index-hdi
23. UNESCO 2021, COVID-19, Education Response, Retrieved from. https://en.unesco.org/covid19/educationresponse
24. Verma, A., Prakash, S.: Impact of COVID-19 on Environment and Society. Journal of Global Biosciences **9**(5), 7352–7363 (2020)
25. Weinzweig, P.A.: The ten commandments of personal power. N.Y., Meridian Press, Creative strategies for shared happiness and success (1988)
26. WHO (World Health Organ.) (1948) Preamble to the Constitution of the World Health Organization as adopted by the International Health Conference, New York, 19–22 June, 1946
27. WHO (World Health Organ.) (2020) Physical and mental health key to resilience during COVID-19 pandemic. WHO Regional Director for Europe, Copenhagen, Denmark
28. Wulff, K., Donato, D., Lurie, N.: What is health resilience and how can we build it? Annu. Rev. Public Health **18**(36), 361–374 (2015)
29. Yunus, A.P., Masago, Y., Hijioka, Y.: COVID-19 and surface water quality: Improved lake water quality during the lockdown. Sci. Total Environ. **731**, 139012 (2020)
30. Zander, S., Venter, Z.S., Aunan, K., Chowdhury, S., Lelieveld, J.: (2020) COVID-19 lockdowns cause global air pollution declines. PNAS **117**(32), 18984–18990 (2020)

Use of Remote Sensing and GIS Techniques for Adaptation and Mitigation of COVID-19 Pandemic

Hemant Bherwani and Rakesh Kumar

Abstract The globe has been caught off guard by COVID-19, which is caused by SARS-CoV-2. With the globe already facing global issues, the pandemic, which began in Wuhan in December 2019, put tremendous pressure on the scientific, political and medical communities, compelling them to search for a vaccine in a matter of months. The pandemic also provided an opportunity for researchers to try and test the latest tools and techniques to manage this crisis. Right from medical scientists to mathematical modelers, the fraternity was engaged in rigorous work to control and mitigate the spread of this virus. The current chapter discusses the use of advanced tools such as Geographic Information System (GIS) and Remote Sensing (RS) to devise adaptation and mitigation strategies for the control of such pandemics. Case studies from various states of India are discussed to explain the controlling strategies which can be developed from these tools and techniques. Remote sensing data from various satellites are discussed to showcase its utility for such crucial times, whereas, GIS tools such as Voronoi Diagram (VD) and ArcPy are discussed as strategic tools for controlling and mitigating the spread of the virus.

Keywords COVID-19 · GIS · Remote Sensing · Voronoi Diagram · Adaptation · And Mitigation

1 Introduction

COVID-19 is a current worldwide communal health disaster that has caused significant mortality and morbidity [1, 2]. To control the spread of this disease, healthcare organizations, from local hospitals to the World Health Organisation (WHO), need resources that can increase the speed and ease of communication [3]. Since all of the

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analytical methods available for detecting virus spread, identifying hotspot areas, and fighting this disease have their limitations in the current pandemic scenario, there is a need for fast and cost-effective predictive and diagnostic tools [3, 4]. Advanced tools such as Remote Sensing (RS) and Geographic Information System (GIS) have already got hold of their roles in the contemporary situations since it manifests a myriad of applications in pandemic management. Simply put, GIS is a digital information system that can combine, cache, modify, scrutinize and organize geo-referenced information hence called spatial data management systems. Imprints of its significance are well evident in the field of public health, mental health, healthcare services & environmental health management [5]. The intervention of GIS in the field of health has created a revolutionary trend, henceforth it can be well utilized as a support system for the identification of trails of COVID-19 cases during this global pandemic [6]. Current research domains of GIS encompass the ability to perceive the COVID-19 phenomenon, its spatial data, spatial and temporal dimensions and its geographic effect on decision-making, social interactions and predictive analytics of the disease's evolution. The specialized agency of the United Nations which oversees the international public health known as the WHO even takes advantage of the various applications of GIS technology to track and keep records regularly and precisely on their dashboards about the number of covid cases and deaths occurring globally. Spotting of COVID-19 outbreak even took place quicker with the spatiotemporal algorithms present in GIS. The estimation and documentation of the relevant number of virus-infected people are the important functionalities of such algorithms. GIS, in conjunction with remote sensing, offers real-time aerial and satellite photographs, allowing for the assessment of disease progression and variability around the globe or in a specific region [7].

The data gleaned by GIS can be used to evaluate and identify the locations that are the most severely infected, as well as locations that are in a high-risk region prone to rapid virus spread in the future. Formulation of stern pandemic management protocols can be done in time in high-risk zones where virus infection created drastic effects with the aid of the GIS technique since it offers timely awareness of the spread of COVID-19 [8]. Using spatial analysis in GIS, disease risks, trends of time and space epidemics and hotspot infections can all be identified [9]. The disease incidence and disease control in various countries can be well comprehended with the help of parametric and probabilistic modelling along with statistical tools available with GIS. To better understand the relationship between COVID-19 cases and population density in the area, a GIS-based Voronoi Diagram (VD) or Thiessen Polygon (TP) is formed to determine the limits of danger zones. The GIS-based VD specifies that it can be used as a guiding tool for the declaration of high-, medium- and low-risk zones based on the polygons. The zones are to be defined based on the spread of COVID-19 cases and the corresponding population of the region [10].

GIS technology extends its application for contact tracing, emergency treatment unit site selection and digital mapping that illustrates the location and time-sensitive functions straightaway associated with a spread of the virus. As a result, administrators will be notified and the specified public event will be postponed, limiting the number of people who will be affected. Issues created by increased demand for medical instruments can be solved in advance with the assistance of web mapping giving a prior indication to the distributors [11]. Some of the research uses GIS and modelling approaches to access the relationship between environmental variables including air pollution and microclimate, as well as their impact on SDGs, and COVID-19 occurrence [12]. Various GIS-based mobile/Android applications developed by a variety of countries are used to trace any infected persons' contacts. Arogya setu (India) and COVID-19 symptom trackers are some of the examples among them [13]. These applications are more cost-effective, provide reliable statistics and are therefore more dependable. Nowadays, municipal sewage test results are utilised to detect the presence of viruses and data acquired from mass testing in the selected area is integrated into the city's GIS system that helps make critical decisions [14].

With the advent of RS, a science that uses satellite imageries and aerial images to collect information about earth surfaces without making direct contact, significant changes have occurred in a wide spectrum of fields. These fields cover Earth science discipline areas along with military, intelligence and economy, commercial, planning and humanitarian applications. In that sense drones or Unmanned Aerial Vehicles (UAVs) which follow the same science extends numerous applications in the pandemic management activities during the COVID-19 outbreak. One of the recent researches work proposed a UAV-based smart healthcare system for COVID-19. The proposed system includes diverse activities such as monitoring, sanitization, social distancing, analysis of data and generation of statistics for the control room. Moreover, the implementation results of the proposed UAV-based smart healthcare system in Delhi/NCR regions illustrate that it is found well efficient and effective in managing COVID-19 operations and prior decision making since the system can cover large distances in a short period [15].

For evaluating the efficiency of regulations created to stay at home and social distancing the satellite imageries procured from RS technology can be utilized at a local as well as global scale. Satellite images provide an idea about what's going on (or not going on) in metropolitan areas, tourist hotspots, roads, production plants and other locations that are considered to be busy on regular days [16]. The intense urge to mitigate the effects of the pandemic always engaged the researchers in developing innovative mechanisms/systems with the available advanced tools. Concerning this, for successful risk alleviation, a COVID-19 Risk Assessment and Mapping (CRAM) model was proposed in recent times which integrates the two important domains of a pandemic such as Hazard and Vulnerability. It uses a GIS-based risk alleviation procedure for the quantification of COVID-19 Risk indices (C19Ri) for the area of interest. So many factors have been established to influence the COVID-19's mortality and disease, according to existing knowledge. A range of hazards, biophysical and socioeconomic factors are used to determine a region's inherent threat of COVID-19 infection. This method can be used to prioritize territories for choices about control and containment. As a result, this strategy offers long-term COVID-19 risk management opportunities, ensuring that the growth and environment of the research area experience hurdles as little as possible [17]. Aside from that, different statistical studies have lately been conducted to be used as a tool to aid in the management of the epidemic. A recent study uses the Susceptible-Exposed-Infectious-Removed (SEIR) model to assess the development of COVID-19 in India and identify the effects of socio-behavioral factors, particularly social distancing. It also explains the relationship between environmental factors and their influences on COVID-19 cases [18]. Air pollution in a location is exacerbating the worldwide burden of mortality attributable to COVID-19, according to the data evaluated by statistical methodologies such as analysis of variance and regression models [19]. However, taking into consideration its chemical properties, shape and particle size, as well as its widespread distribution on practically all surfaces, Particulate Matter (PM), can play a significant role in pathogen transmission via air, water and by contact [20]. Another issue associated with the pandemic is the appropriate disposal of Personal Protective Equipment (PPE) by frontline staff, as it is a possible source of infection. Decentralized incineration has been determined to be sustainable both for the ecology and for human health, with the goal of safe waste disposal and preventing disease spread from such equipment [21].

Among the countless application of RS and GIS, the above-mentioned information only gives a glance at the utilization of RS and GIS in the field of pandemic management. These advanced tools are still developing and extending their functionality not only to tackle the current situation but also in all the fields closely associated with them.

2 Prime Focus of the Proposed Chapter

The proposed chapter focuses on mitigation strategies to reduce the spread of the virus with specific attention to Remote Sensing and GIS-based techniques and describes the case study of Indian States. There are various tools in GIS and remote sensing, which can help in developing adaptation and mitigation steps for such a pandemic. The major objectives of the research work are as follows:

- Use of GIS for Pandemic Management:
  The section will discuss how GIS is involved in pandemic management strategies and explains the use of advanced tools like Voronoi Diagram and ArcPy for identification of vulnerable zones to devise a targeted strategy for containment, buffer and open zones. Indian states shall be analyzed for showcasing the hypothesis and results.
- Use of Remote Sensing tools for Adaptation and Mitigation:
  The section will discuss the employment of satellite data such as Moderate Resolution Imaging Spectroradiometer (MODIS) and analyze the results to showcase the application of RS to illustrate the effects of pandemic control strategies in the environmental quality. It will demonstrate the use of Remote Sensing data for adaptation towards the pandemic. The mechanism shall be demonstrated using a case study.

3 Applications of GIS for Pandemic Management

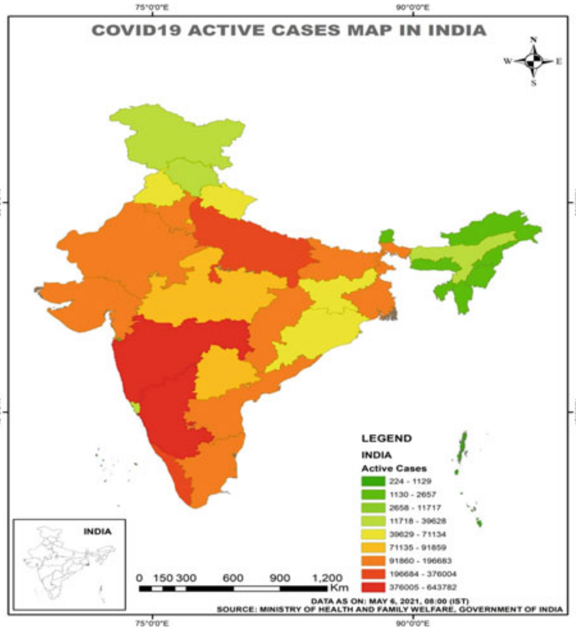
According to the Dictionary of Epidemiology the explanation for the term "pandemic" which is accepted globally is "an epidemic occurring worldwide, or over a very wide area, crossing international boundaries and usually affecting a large number of people". A pandemic is defined by its wide geographic spread, disease movement, novelty, severity, high attack rates and explosiveness, minimal population immunity, infectiousness and contagiousness. When a pandemic strikes, the equilibrium of a well-balanced culture is disrupted in every way. A pandemic would impact health, as well as economic, social and security consequences. During a virus outbreak, emergency responses would be required, including shorter path tracing for health and medicine facilities, vaccination center mapping, isolation center mapping and recognition of hotspot areas and confirmed infected cases. Systematic and productive emergency response will minimize death and disability, as well as the socio-economic consequences. To cope efficiently with epidemic outbreaks and pandemics now and in the future, policymakers will need to figure out how to provide a proper and well-structured emergency response system [22].

By showcasing its implementations in selected Indian cities, the following section discusses how advanced tools in GIS contribute to pandemic management activities and how they can be employed to tackle the situation for the adaptation and mitigation of the COVID-19 pandemic.

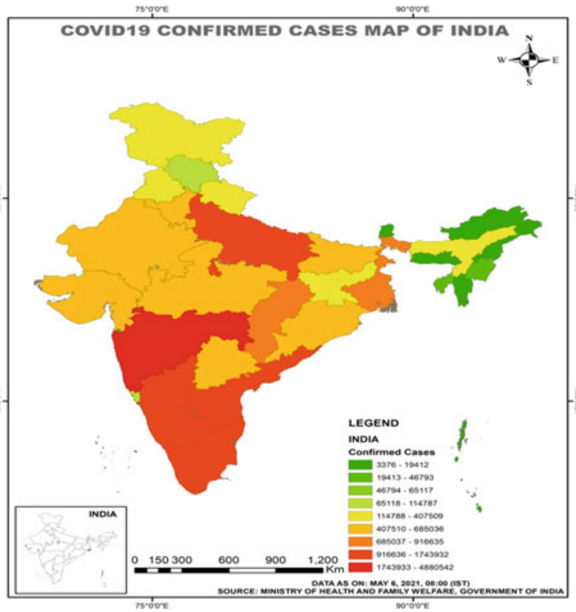
3.1 GIS-Based Analysis of COVID-19 for Understanding the Spatio-Temporal Spread of Infections

GIS, a versatile comprehensive framework that offers provisions for delineating and tracking the Spatio-temporal diffusion of contagious diseases. GIS can permit epidemiologists to plot the current and earlier incidence of diseases jointly with several other variables signifying the surroundings, natural features and population statistics of a region. This information may assist in the understanding of outbreak source as well as the distribution trend and severity. Hence the execution of suitable measures for the control of disease, defensive and inspection measures can be implemented. During the disease outbreak, the GIS network devised quick approaches for visualizing COVID-19 data, tracing virus-infected cases in space and organizing and managing resources to meet fundamental community requirements [23]. The following Fig. 1a, b represents the Active and Confirmed cases in India created with the available tools in GIS.

The Ministry of Health and Family Welfare (MoHFW), Government of India updates all information concerning the pandemic in their dashboard and provides data regarding Active, Confirmed & Death cases along with the total number of vaccinations done [24]. A "Confirmed case" can be defined as a person who tested positive for the confirmatory test of COVID-19 virus infection and is considered



(a)



(b)

Fig. 1 COVID-19 (**a**) Active cases map of India (**b**) Confirmed cases map of India to be contagious. Moreover, it is possible that a COVID-19 case can be considered as a "Probable case" if there is a risk to have a COVID-19 infection or if the person has a present COVID-19 virus infection but not confirmed by a confirmatory viral test. A "Confirmed case" or a "probable case" are both "Active cases" [25, 26]. To develop COVID-19 Active & Confirmed cases map case statistics of each state as of May 6th 2021 were collected from the MoHFW. Using ArcGIS 10.6 the dataset collected from the above-mentioned source is coupled with the Indian state boundary shapefile attributable table and is correlated with the state-wise data. The GIS Symbology Toolset provides classification & colour coding provisions and accordingly the Active & Confirmed cases maps of India are developed. Jenks natural breaks classification method is used for developing Active & Confirmed COVID-19 cases map with 9 classes in each map. It is a data cluster approach for determining the best way to group values into various categories [27]. As per the datasets, the states having Low & High Cases scenarios are visible with color-coding.

Figure 1a, b shows that Maharashtra and Karnataka have high active case scenarios. It is followed by Kerala and Uttar Pradesh. Maharashtra is the top state in terms of confirmed cases. The south Indian states, wise Kerala, Karnataka, Andhra Pradesh, Tamil Nadu and Uttar Pradesh holds the second position after Maharashtra in terms of confirmed cases. It is clearly evident from the analysis that states having high population density or very active lifestyles have higher number of cases. In comparison to other states, the active and confirmed cases in the eastern states of India are very low. The analysis of these types of maps aids in determining the current state of the pandemic, its magnitude and guides making prior decisions and procedures for disease control.

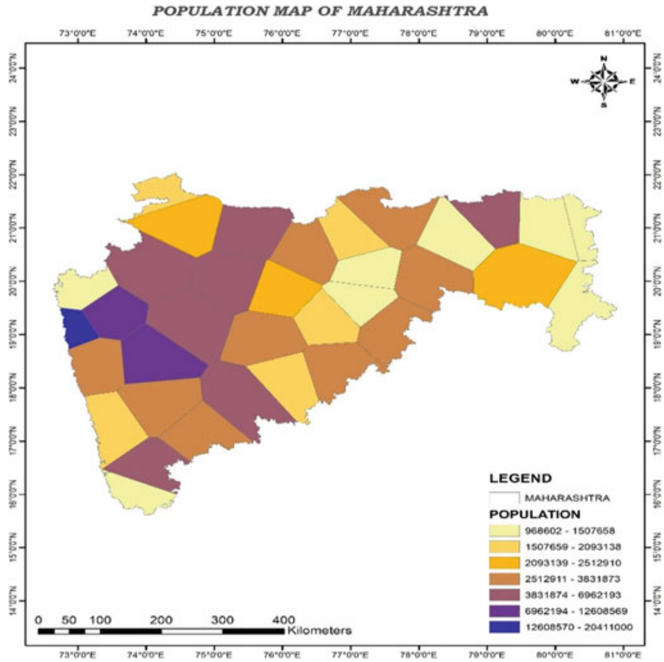
3.2 GIS-based Voronoi Approach and Bayesian Probabilistic Modeling for Understanding COVID-19 Transmission

To monitor the progression of the disease, major initiatives such as clinical trials of drugs and vaccinations, social distancing, and the use of PPE are being introduced. A recent research work highlighted the Indian government's lockdown and social distancing policies and assesses their efficacy using a Bayesian Probability Model (BPM). According to the Change Point Analysis (CPA) performed using the aforementioned method, indicates that introduction of the lockdown before the rapid increase in cases was competent to control the epidemic much more effectively and efficiently. The above-stated study is unique as it employs the BPM to analyze the evolving phase of COVID-19 transmission across states. The borders of zones of risk can be defined by constructing TP. GIS-based VD or TP is formed to evaluate the relationship between cases of COVID-19 and the density of population in the study area. The study establishes a new concept for using probabilistic modelling and tools based on GIS to comprehend COVID-19's situation.

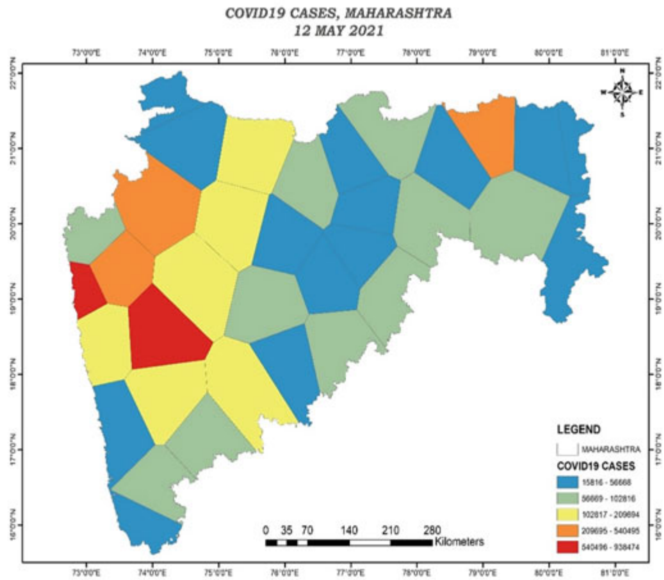
CPA is carried out to truly comprehend the virus's spread, the outbreak's function, and the possible measures used in area of interest. The COVID-19 tracker can be used to acquire estimates of COVID-19 cases in various Indian states. CPA is used to calculate the inflection point for COVID-19 events in each state using the data regarding the weekly cumulative statistics of COVID-19 cases in a study region. Bayesian modelling can be done with the PyMC3 package. The number of sampling points is used to establish Bayesian inference. PyMC3 is a recent open-source Python Probabilistic Programming (PP) package that is better suited for Bayesian statistical models. Determination of Delta (Δ) can be done by taking the data regarding the state's first case and the date of lockdown concerning the respective state's change stage. Delta is a metric that gauges how swiftly states responded to the virus's spread. By the time lockdown was implemented, disease transmission had already increased in many states. Delta assists in recognising the time period preceding the rapid disease progression that goes out of hand. The population, population density, and area are employed as study parameters in connection to the delta. Cases per unit population (CPP), cases per unit population density (CPD), and cases per unit area (CPUA) can be measured and correlated with delta using linear Pearson's correlation, with t-tests proving the significance of the correlation. For hypothesis testing, a statistical tool such as two-sample t-tests aids to compare the mean of two independent parameters. Under the assumption of normality of the dataset and equality of variance, this parametric test method helps determine the mean difference between test groups equal to 0 as the null hypothesis (vs $\neq 0$ as an alternative hypothesis). To determine the significance of the tested parameter, the test can be performed with a 95% confidence interval. To analyze the normality of the distribution, the kurtosis and skewness values can be noticed. The above-mentioned study of factors related to population and delta provides an insight into the fundamental factors that lead to virus transmission.

The same data which is collected for the execution of BPM is applied to create the VD or TP for a given study area and here Maharashtra and Karnataka states have been studied. VD or TP is built for the analyzed states in an attempt to comprehend the areas of intervention amongst these regions. The polygon, in a sense, acts as a hotspot for the COVID-19 instances. TP is a fundamental tool for evaluating neighborhood and proximity. Since TPs are made up of a series of sampling points, each polygon defines an impact region that surrounds its sampling point. The nearest point is assigned space using TPs. In this scenario, the goal of employing polygons is to determine where the area's potential safe zones and hot spots are. TP can be generated in ArcGIS using the software's built-in tool. The data for each point in the tool, as well as its position, is entered. The shape of the polygon is determined by the position, while the color represents the data's intensity or magnitude. For ease of understanding, the color-coding has been kept consistent across the states. For each state, TP is prepared for the population and COVID-19 situations. The following Figs. 2a, b and 3a, b illustrates the study results obtained for Maharashtra and Karnataka states.

A high rate of population statistics can be seen in the western side of Maharashtra and consequently high rate of COVID-19 cases are there which are presented on a log scale in the above maps. Eastern Maharashtra holds a medium range of population and COVID-19 cases. However, in the southern part, the population is greater than a



(a)



(b)

Fig. 2 (**a**) Population and (**b**) Thiessen polygon map of COVID 19 cases in Maharashtra

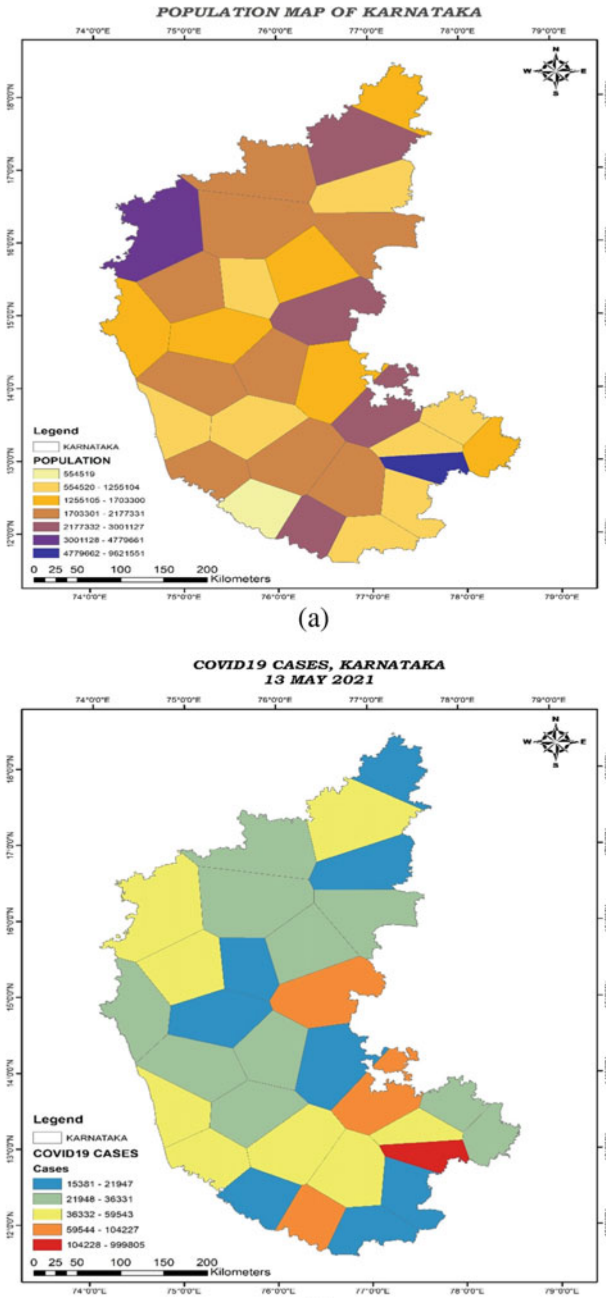


Fig. 3 (**a**) Population and (**b**) Thiessen polygon map of COVID 19 cases in Karnataka

medium-range while the COVID-19 cases fall under the medium-range. COVID-19, which is an indication of distress, is already creeping in towards the eastern side, which is intriguing to see.

The population in the southern part of Karnataka is high compared to the northern part. The coastal side of Karnataka possesses a medium range of population statistics. However, the COVID-19 circumstances are found high in the southern part and while a medium-range is there in northern Karnataka. The spreading is slowly moving towards the coastal and northern sides. These kinds of data are useful because they estimate the potential transmission pathway and assist decision-makers in issuing proper alerts to the areas which are likely to be affected and providing advance warnings for managing COVID-19 outbreaks. It should also be mentioned that places with large populations have a high rate of infected cases.

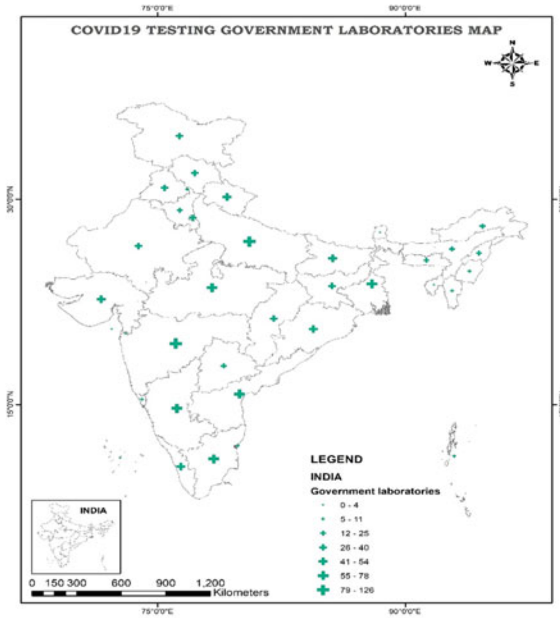
3.3 GIS-Based Analysis for Understanding the Statistics of Accessible COVID-19 Testing Centers

If a rapid diagnosis of the infection is possible, a pandemic and its potential spread can be halted immediately. For this aim, an area should be equipped with sufficient testing laboratories with sufficient testing capacity to allow for the diagnosis of a large populace in the event of an uncontrollable virus outbreaks. Testing laboratories with facilities that provide test results in a more timely manner plays an important role in infection control. GIS tools can be used to analyze and depict the magnitude of accessible COVID-19 testing centers in a region.

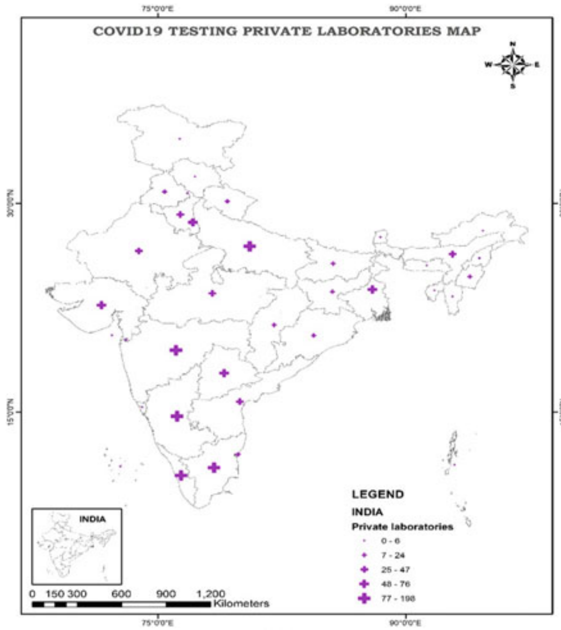
The Indian Council of Medical Research (ICMR) always updates the information regarding the state-wise number of COVID-19 testing laboratories (Both Government and Private) reporting to them in their dashboards. The information gathered is used to create maps depicting the number of COVID-19 testing centers that are accessible. The quantitative information is shown in the Indian map using ArcMap 10.6 and a graded symbol renderer. It permits quantitative values for a field to be organized into ordered classes, with each class given a graded symbol ranging from smallest to largest. Graduated symbology, which is one of the classification methods available in ArcGIS, is used for classifying numerical fields and provides a better overview. The following maps in Fig. 4a, b portrays the Government and Private COVID-19 testing centers in India developed using GIS techniques.

It can be seen that Maharashtra and Uttar Pradesh have the most government testing labs, while Sikkim and Tripura have the fewest. In Kerala, Tamil Nadu, Karnataka, Maharashtra and Uttar Pradesh, the number of private testing labs is larger, whereas it is lower in Jammu and Kashmir, Himachal Pradesh and most of India's eastern states. It is evident that the number of screening facilities in India's eastern states is relatively low. The use of such maps allows administrators to focus their attention on areas that lack such amenities. The analysis allows for the establishment

Fig. 4 (**a**) Government and (**b**) Private COVID-19 testing laboratories in India



(a)



(b)

of testing facilities based on population density and virus outbreak severity in a region in advance.

4 Applications of Remote Sensing Tools for Adaptation and Mitigation

The changes brought by the pandemic in the normal social life of a community and the resultant difficulties that emerged were not small. Social distancing, Lockdown and Quarantine associated with the pandemic all were new to the society and have hampered the balance of the same in all respects. However, it imparted some benefits in terms of air quality improvement. Extensive research has been conducted in recent times to demonstrate the effects of lockdown in improving air quality. Satellite imageries procured from RS technology along with ground-based data play a vital role in the understanding of air quality improvements associated with the lockdown policy of the government.

The RS technology manifests numerous applications; however, it can be well utilized to estimate the after effects of a pandemic in the environmental quality. The following section illustrates the application of RS to extract Aerosol Optical Depth (AOD) data of Maharashtra and Karnataka states during the pre-lockdown and lockdown period. Aerosols are microscopic solid and liquid particles floating in the environment which occurs due to natural causes as well as anthropogenic activities. Certain aerosols can be detrimental to individuals and communities if inhaled. The study period selected for the current study is 2019 and 2020. $PM_{2.5}$ is considered to be a major air pollutant that develops and aggravates respiratory illnesses in humans. Hence the study of its concentration in the environment is important during such a pandemic since the virus adversely affects the person already having the illness. Ground-based monitoring stations to gauge the $PM_{2.5}$ levels at higher frequencies in ambient air are installed globally in most of the major cities, however, to understand its spatial distribution, these systems are insufficient [28, 29]. By coupling AOD and meteorological variables, a new approach for predicting the $PM_{2.5}$ level in the environment is used in this study. Traditional $PM_{2.5}$ field measurements are hard to procure spatial data, particularly at the precise scale necessary to determine the volatility of high-density cities. RS technology extends its application to estimate the aerosols and aids in the assessment of $PM_{2.5}$ where ground estimates are not possible [29, 30]. The AOD data are collected with the help of MODIS. Since the AOD is easier to produce, it has been the most commonly used technique in statistical models to forecast $PM_{2.5}$ levels in the environment [31, 32].

For the Maharashtra and Karnataka states the MODIS AOD data is extracted for the desired study period from Level 1 and Atmosphere Archive and Distribution System Distributed Active Archive Centre (LAADS DAAC) and AOD is estimated accordingly. Conversion of AOD data to $PM_{2.5}$ measurements are done by Simplified Aerosol Retrieval Algorithm (SARA) binning model with low surface pressure period equation [$PM_{2.5} = 110.5\ [SARA\ AOD] + 12.56$] and the model is validated [33]. The model offers a high degree of correlation between AOD and $PM_{2.5}$ measurements and is dependent on meteorological parameters. It also improves the meteorological dimensions of the $PM_{2.5}$ prediction model's regression coefficient. Numerous equations are developed for each meteorological parameter in binning method to precisely predict the $PM_{2.5}$ measurements [34]. Among these the above method equation holds better prediction. The model has good correlation, accurate slope, low intercept, low error and can accurately represent the spatial distribution of $PM_{2.5}$ at 500 m resolution in urban areas. The following Fig. 5 represents AOD data extracted for Maharashtra state and Fig. 6 represents the same for Karnataka state for the year 2019 and 2020 respectively.

Analysis of the maps provided in Figs. 5 and 6 reveals a considerable reduction in the $PM_{2.5}$ levels in Maharashtra and Karnataka states. The higher value of AOD falls to 0.72 in 2020 from a value of 0.92 in 2019 for Maharashtra while it is 0.52 and 0.62 respectively for Karnataka state. Analysis of these values convey that a substantial reduction in $PM_{2.5}$ levels has occurred in this state and are brought about by the concerned authorities' lockdown methods, which resulted in the cessation of all operations and anthropogenic activities. As a result, there is a noticeable improvement in the environment, which may indicate favourable trends in the community's general health.

Apart from this Drones or Unmanned Aerial Vehicles (UAVs) which function through RS technology have been deployed for extensive applications by several countries during COVID-19 situations. During a pandemic like this, where the possibility of infection by a highly contagious virus is high, the employment of drones for various management methods is greatly acknowledged since it involves only minimum human interactions and can reach remote areas. "Cyient" is a global technology solutions company that extended unmanned aerial spectrum monitoring technology to Telangana police during such a pandemic to support the management of lockdown strategies. Furthermore, a Hyderabad-based start-up known as "Marut drones" just introduced a series of drones to battle India's COVID-19 problem. Drones are used for crowd control, public announcements, mass screening, disinfectant spraying and the delivery of medical supplies and other necessities, to name a few. Surveillance drones are fitted with cameras installed, allowing the police to properly observe vulnerable parts of towns and respond quickly to any inappropriate scenario. Drones, in conjunction with crowd observation, can be extremely useful for transmitting crucial information, especially in areas where connectivity is limited. Thermal imaging drones can be used to measure the temperature of multiple individuals at once, something that an infrared thermometer can't do because it only examines the temperature of one person at a time. Using drones to spray disinfectants in virus-infected areas can help lower the risk of an infection epidemic while also limiting the virus's interaction with service people. Drones can be used to transport medical supplies from one medical centre to another, as well as from medical centres to patient's location [35].

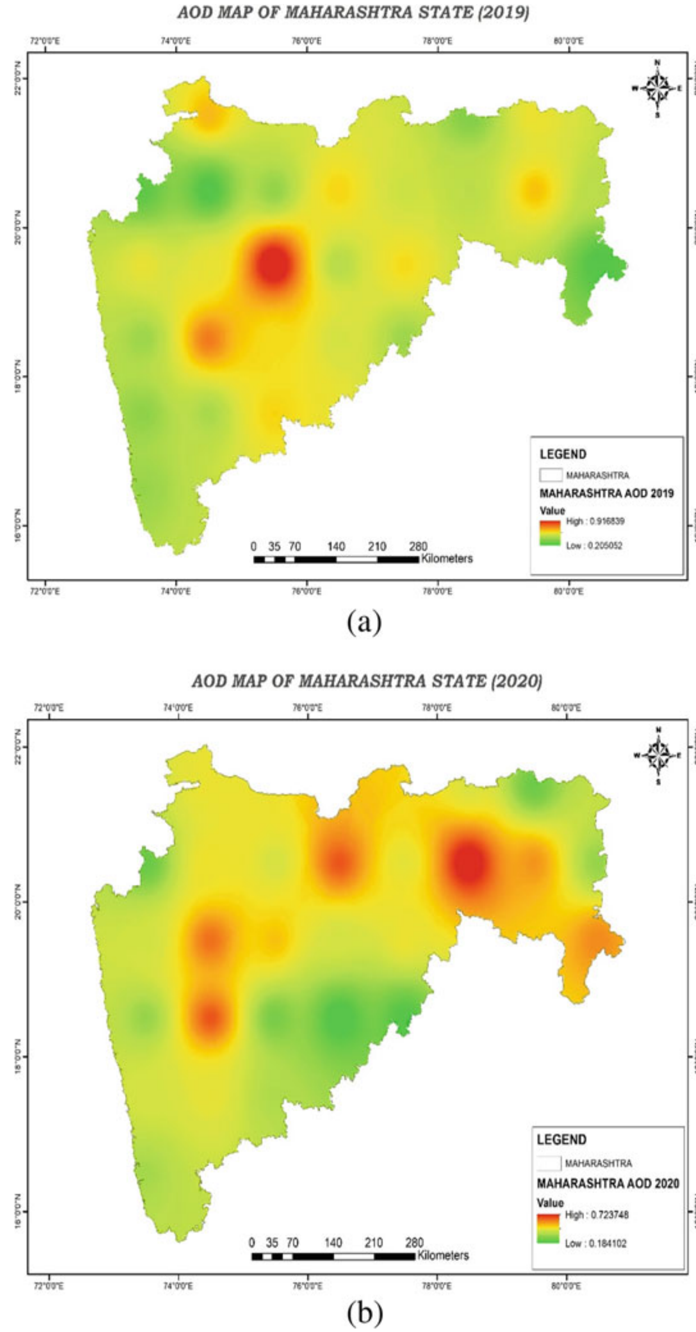


Fig. 5 AOD Maps of Maharashtra for the years 2019 & 2020

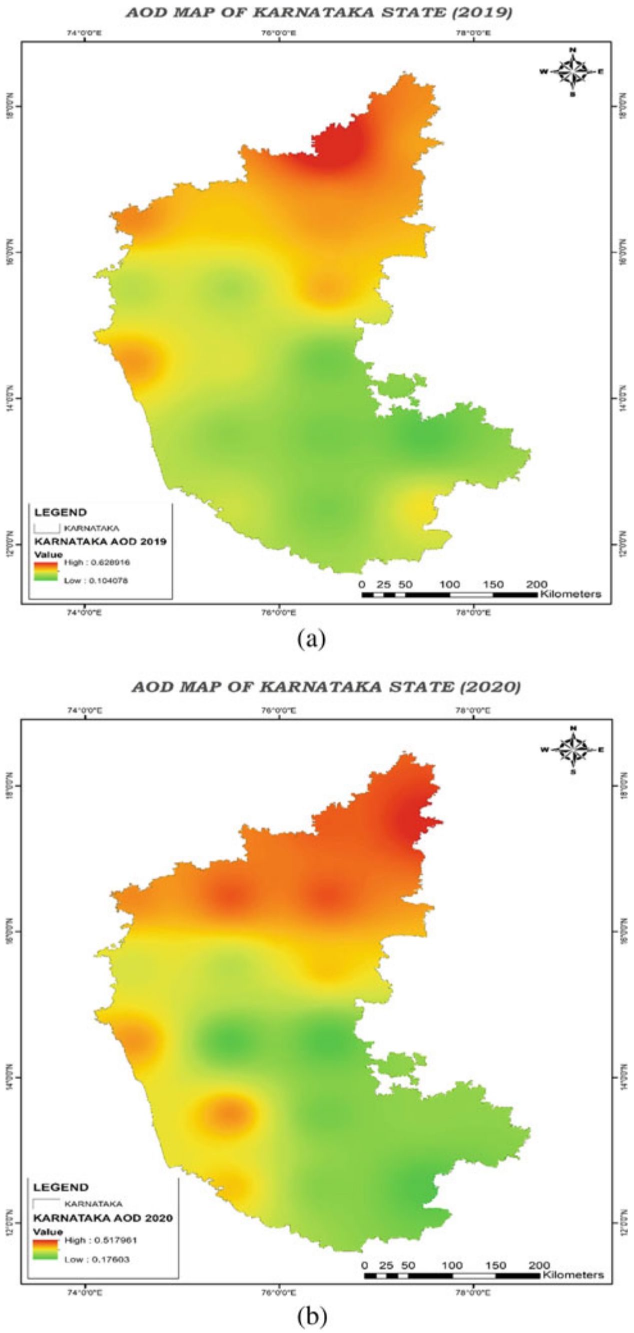


Fig. 6 AOD Maps of Karnataka for the years 2019 & 2020

Drones make it feasible to deliver samples, blood, vaccinations, drugs, organs and life-saving medical devices. It also aids in the identification of relevant geo-referenced data on climate aspects and other parameters that affect contagious disease spread. Because of the necessary need for social distance to control virus transmission, there has been a surge in internet purchases and digitally enabled delivery systems that do not require direct physical touch. As the need for no-contact distribution has grown, autonomous transport technologies, such as unmanned aerial vehicles or drones, have received increasing attention from government, organizations and authorities [36]. Numerous countries are currently well involved in using these devices in various fields and significant changes are being made in their designs in conjunction with modern technology to smoothly handle a difficult condition such as this. RS can also make health data available instantaneously for the doctors and clinicians in ambulances and other on-the-go treatment centres and in several occasions to assist the service staffs on their jobs in real time. With remotely sensed data in effect, healthcare may operate with greater coordination among multiple facilities owing to legitimate data sharing and accessibility to real patient status reporting. Better integration will almost certainly lead to a better field as a whole.

5 Conclusion

Pandemics and their spread always strike unexpectedly and without warning. They spread quickly, wreaking havoc on society's health, security, social and economic well-being. New diseases evolve over time that the human species is completely unaware of. As a result, society should be well-equipped with the fundamental necessities that can be used on time so that the pandemic effects on all sectors can be dampened to some extent. Proper pandemic management is also required to reduce the consequences of a pandemic. The efficiency of pandemic management is governing by a number of criteria, ranging from timely administration to technology deployment.

The applications of advanced technologies like GIS and RS and their utility in the various situations of a pandemic discussed in the above sections reinforce their importance in such crucial circumstances. The capabilities available in GIS technology may be used to analyse the number of infected cases, estimate potential transmission routes and determine the number of available testing centres. Such information is crucial for establishing the current state of the pandemic, the rate of transmission and whether the testing facilities available in a given location are enough. It allows the administrator to issue a pre-alert in a region that is likely to be affected by the virus, as well as select what kind of control tactics to use in regions that have already been afflicted by the epidemic. Analysis of GIS-generated maps allows for the establishment of new testing laboratories in areas where these facilities are scarce. The RS application sheds light on the improvement in environmental quality that has been achieved as a result of the mitigation strategies proposed by the concerned authorities. COVID-19 hurts people who already have respiratory illnesses; therefore, pollution rate analysis and control are an inescapable component of the current situation. It is also worth noting that areas with large population figures have a higher prevalence of diseases as a result of pollution emissions caused by anthropogenic activity. RS can be used to assess the effectiveness of declaring confinement zones and lockdown control techniques. Drones or Unmanned Aerial Vehicles (UAVs) powered by RS technology have shown a wide range of uses for smooth pandemic control in a variety of countries. It included everything from well-managed congestion in affected areas to the distribution of needed commodities to those in need in inaccessible areas, all intending to reduce the community's hardships at such a critical time.

6 Suggestions and Future Perspective

For the contemporary health care industry to work more quickly and productively, geo—spatial technology is highly vital. Location-based intelligence, recognizing patterns of health, monitoring the transmission of contagious diseases, displaying medical and health data through RS & GIS are some of the common applications covered under this technology. The impact of these tools in health and healthcare systems is growing. The applications of these tools in this sector have a promising future. The growing emphasis on healthcare data, as well as the spatial data held among them, can offer up plenty of growth opportunities for public health analysis. Apart from the above-mentioned applications their usefulness is yet to be explored more and should be investigated to spread their functionalities for the betterment of mitigation strategies and efficient decision making. A country's officials should focus on research initiatives in order to improve existing applications and establish relevant strategies to concentrate on developing tailored, user-friendly systems to meet specific requirements while preserving a framework for sharing important data throughout the whole health and welfare sector. The impending growth of these technologies and their integration into healthcare systems will result in a breakthrough in the realm of pandemic management.

References

1. Mohanty, S.K., Satapathy, A., Naidu, M.M., Parwani, A.V.: Severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) and coronavirus disease 19 (COVID-19) – anatomic pathology perspective on current knowledge. Diagn. Pathol. **15**(103) (2020). https://doi.org/10.1186/s13000-020-01017-8
2. Bherwani, H., Nair, M., Musugu, K., Goutam, S., Gupta, A., Kapley, A., Kumar, R.: Valuation of air pollution externalities: comparative assessment of economic damage and emission reduction under COVID-19 lockdown. Air Qual. Atmos. Health **13**, 683–694 (2020). https://doi.org/10.1007/s11869-020-00845-3
3. Udugama, B., Kadhiresan, P., Kozlowski, H.N., Malekjahani, A., Osborne, M., Li, V.Y.C., Chen, H., Mubareka, S., Gubbay, J.B., Chan, W.C.W.: Diagnosing COVID-19: the disease and

tools for detection. ACS Nano. **14**(4), 3822–3835 (2020). https://doi.org/10.1021/acsnano.0c02624
4. Parvin, F., Ali, S.A., Hashmi, S.N.I., Ahmad, A.: Spatial prediction and mapping of the COVID-19 hotspot in India using geostatistical technique. Spat. Inf. Res. (2021). https://doi.org/10.1007/s41324-020-00375-1
5. Fradelos, E.C., Papathanasiou, I.V., Mitsi, D., Tsaras, K., Kleisiaris, C.F., Kourkouta, L.: Health based geographic information systems (GIS) and their applications. Acta Inf. Med. **22**(6), 402–405 (2014). https://doi.org/10.5455/aim.2014.22.402-405
6. Singhal, C., Dubey, A., Mathur, A., Pundir, C.S., Narang, J.: Paper based DNA biosensor for detection of chikungunya virus using gold shells coated magnetic nanocubes. Process Biochem. **74**, 35–42 (2018). https://doi.org/10.1016/j.procbio.2018.08.020
7. Franch-Pardo, I., Napoletano, B.M., Rosete-Verges, F., Billa, L.: Spatial analysis and GIS in the study of COVID-19, a review. Sci. Total Environ., **739**, 140033 (2020). https://doi.org/10.1016/j.scitotenv.2020.140033
8. Saran, S., Singh, P., Kumar, V., Chauhan, P.: Review of Geospatial Technology for Infectious Disease Surveillance: Use Case on COVID-19. J. Indian Soc. Remote Sens. **48**(Issue8), 1121–1138 (2020). https://doi.org/10.1007/s12524-020-01140-5
9. Karuppannan, S., Murugesan, B., Alemayehu, T.M., Ranganathan, M., Gnanachandrasamy, G., Raj, B. Distribution and trend analysis of COVID-19 in India: geospatial approach. J. Geogr. Stud. **4**(1), 1–9 (2020). https://doi.org/10.21523/gcj5.20040101
10. Bherwani, H., Anjum, S., Kumar, S., Gautam, S., Gupta, A., Kumbhare, H., Anshul, A., Kumar, R.: Understanding COVID-19 transmission through Bayesian probabilistic modeling and GIS-based Voronoi approach: a policy perspective. Environ. Dev. Sustain. (2020). https://doi.org/10.1007/s10668-020-00849-0
11. Sarwar, S., Waheed, R., Sarwar, S., Khan, A.: COVID-19 challenges to Pakistan: is GIS analysis useful to draw solutions? Sci. Total Environ. **730**, 139089 (2020). https://doi.org/10.1016/j.scitotenv.2020.139089
12. Bherwani, H., Gautam, S., Gupta, A.: Qualitative and quantitative analyses of impact of COVID-19 on sustainable development goals (SDGs) in Indian subcontinent with a focus on air quality. Int. J.Environ. Sci. Technol. **18**(4), 1019–1028 (2021)
13. Boulos, M.N.K., Geraghty, E.M.: Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: how 21st century GIS technologies are supporting the global fight against outbreaks and epidemics. Int. J. Health Geogr. **19**(1), 8 (2020). https://doi.org/10.1186/s12942-020-00202-8
14. https://www.gislounge.com/how-gis-easing-covid-19-lockdown-restrictions/
15. Kumar, A., Sharma, K., Singh, H., Naugriya, S.G., Gill, S.S., Buyya, R.: A drone-based networked system and methods for combating coronavirus disease (COVID-19) pandemic. Futur. Gener. Comput. Syst. **115**, 1–19 (2021). https://doi.org/10.1016/j.future.2020.08.046
16. Bhattacharjee, T., Bhattacharjee, I.: A review: how space technology can help in COVID-19 pandemic (with reference to remote sensing and GIS). J. Remote Sens. & GIS. **10**(3), 1000286 (2021)
17. Kanga, S., Meraj, G., Sudhanshu, Farooq, M., Nathawat, M.S., Singh, S.K. Analyzing the risk to COVID-19 infection using remote sensing and GIS. Risk Anal. **41**(5), 801–813 (2021). https://doi.org/10.1111/risa.13724
18. Bherwani, H., Gupta, A., Anjum, S., Anshul, A., Kumar, R. Exploring dependence of COVID-19 on environmental factors and spread prediction in India. Npj Clim. Atmos. Sci. **3**, 38 (2020). https://doi.org/10.1038/s41612-020-00142-x
19. Gupta, A., Bherwani, H., Gautam, S., Anjum, S., Musugu, K., Kumar, N., Anshul, A., Kumar, R.: Air pollution aggravating COVID-19 lethality? exploration in Asian cities using statistical models. Environ. Dev. Sustain. **23**, 6408–6417 (2021). https://doi.org/10.1007/s10668-020-00878-9
20. Wathore, R., Gupta, A., Bherwani, H., Labhasetwar, N.: Understanding air and water borne transmission and survival of coronavirus: insights and way forward for SARS-CoV-2. Sci. Total Environ. **749**, 141486 (2020). https://doi.org/10.1016/j.scitotenv.2020.141486

21. Kumar, H., Azad, A., Gupta, A., Sharma, J., Bherwani, H., Labhsetwar, N.K., N.K., Kumar, R.: COVID-19 creating another problem? Sustainable solution for PPE disposal through LCA approach. Environ. Dev. Sustain. **23**, 9418–9432 (2021). https://doi.org/10.1007/s10668-020-01033-0
22. Qiu, W., Rutherford, S., Mao, A., Chu, C.: The pandemic and its impacts. Health, Cult. Soc. **9–10**, 2161–6590 (2016–2017). https://doi.org/10.5195/hcs.2017.221
23. Gangwar, H.S., Ray PKC, P.K.: Geographic information system-based analysis of COVID-19 cases in India during pre-lockdown, lockdown, and unlock phases. Int. J. Infect. Dis. **105**, 424–435 (2021). https://doi.org/10.1016/j.ijid.2021.02.070
24. https://www.mohfw.gov.in/
25. WHO COVID-19: case definitions, updated in public health surveillance for COVID-19. WHO reference number: WHO/2019-nCoV/Surveillance_Case_Definition/2020.2. Published 16 December 2020
26. https://www.nolangroupmedia.com/covid19/confirmed-cases-vs-probable-cases-vs-active-cases-explained/article_c99147e4-b7d4-11ea-a64a-c75fd7670460.html
27. https://mangomap.com/gis-mapping
28. Gomišček, B., Hauck, H., Stopper, S., Preining, O.: Spatial and temporal variations of PM1, PM2. 5, PM10 and particle number concentration during the AUPHEP—project. Atmos. Environ. **38**(24), 3917–3934 (2004). https://doi.org/10.1016/j.atmosenv.2004.03.056
29. Al-Saadi, J., Szykman, J., Pierce, R.B., Kittaka, C., Neil, D., Chu, D.A., MacDonald, C.: Improving national air quality forecasts with satellite aerosol observations. Bull. Am. Meteorol. Soc. **86**(9), 1249–1262 (2005). https://doi.org/10.1175/BAMS-86-9-1249
30. Gupta, P., Christopher, S.A., Wang, J., Gehrig, R., Lee, Y. and Kumar, N.: Satellite remote sensing of particulate matter and air quality assessment over global cities. Atmos. Environ. **40**(30), 5880–5892 (2006). https://doi.org/10.1016/j.atmosenv.2006.03.016
31. Clarke, A.D., Collins, W.G., Rasch, P.J., Kapustin, V.N., Moore, K., Howell, S., Fuelberg, H.E.: Dust and pollution transport on global scales: aerosol measurements and model predictions. J. Geophys. Res. Atmos., **106**(D23), 32555–32569 (2001). https://doi.org/10.1029/2000JD900842
32. Holben, B.N., Tanre, D., Smirnov, A., Eck, T.F., Slutsker, I., Abuhassan, N., Kaufman, Y.J.: An emerging ground-based aerosol climatology: aerosol optical depth from AERONET. J. Geophys. Res. Atmos. **106**(D11), 12067–12097 (2001). https://doi.org/10.1029/2001JD900014
33. Bherwani, H., Kumar, S., Musugu, K., Nair, M., Gautam, S., Gupta, A., Ho, C., Anshul, A., Kumar, R.: Assessment and valuation of health impacts of fine particulate matter during COVID-19 lockdown: a comprehensive study of tropical and sub tropical countries. Environ. Sci. Pollut. Res. (2021). https://doi.org/10.1007/s11356-021-13813-w
34. Bilal, M., Nichol, J.E., Spak, S.N.: A new approach for estimation of fine particulate concentrations using satellite aerosol optical depth and binning of meteorological variables. Aerosol Air Qual. Res., **17**(2), 356–367 (2016). https://doi.org/10.4209/aaqr.2016.03.0097
35. Chamola, V., Hassija, V., Gupta, V., Guizani, M.: A Comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact. Special section on deep learning algorithms for internet of medical things. IEEE Access. **8**, 90225–90265 (2020). https://doi.org/10.1109/ACCESS.2020.2992341
36. Kunovjanek, M., Wankmüller, C.: Containing the COVID-19 pandemic with drones - feasibility of a drone enabled back-up transport system. Transp. Policy **106**, 141–152 (2021). https://doi.org/10.1016/j.tranpol.2021.03.015

Mapping Blockchain Technology Prospects and Solutions in the Healthcare Industry for Pandemic Crises

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Abstract Throughout history, pandemics have extensively impacted humans' lives in many different ways. Despite the World Health Organisation (WHO), governments and supporting health agencies and non-profit organisations' widespread efforts to identify, control, and manage pandemics, such crises are increasing in frequency. Using measures to prevent, address, or overcome them has become challenging and overwhelming. Overall, the current pandemic influenced life, has left scientists, practitioners and politicians no choice other than to find solutions to support societies to live the new normal in a more thriving way. Their focus has been on helping individuals and communities prepare for the 'ad-hoc future' health-related crises. One of the most recent promising discoveries and creative developments that seems to be playing a vital role in everyone's daily life is 'Blockchain Technology'. In recent years, blockchain has received increased interest and has moved beyond finance, and its emergence is revolutionising many industries in various ways. For instance, blockchain has been actively researched and used for multiple purposes such as monitoring supply chains, managing retail loyalty rewards programs, certifying digital credentials, etc. While blockchain has positively disrupted many of the past and current healthcare-related practices, still it's essential to gain an in-depth understanding of blockchain technology's intriguing benefits and open challenges. Such comprehensive knowledge can enhance the development and utilisation of further promising healthcare products/services and processes within societies. This chapter will support the readers in understanding the blockchain technology prospects and solutions for the healthcare industry in general and healthcare-related crises in particular.

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1 Blockchain Technology and Healthcare Industry

Blockchain technology was initially introduced and considered a decentralised ledger for financial transactions, and many business leaders and practitioners saw blockchain and cryptocurrencies as synonymous [16]. In 2014 when Blockchain 2.0 was introduced, mainly the focus was on enhancing smart contracts and financial transactions and later, when Blockchain 3.0 was developed, additional uses, covering a range of non-financial transactions such as healthcare, supply chain, government, and etc. was considered [38].

According to [19], (p. 3) "Blockchain is a distributed ledger shared by multiple parties who can add transactions to the ledger". Blockchain securely stores all records in a peer-to-peer network and verifies transactions by its decentralisation attribute [22]. At its most basic, blockchain allows two or more parties to securely exchange value in digital environments without any intermediary third-party intervention [15, 16, 26, 31]. According to [20], (p. 3), "Blockchain uses public-key cryptographic techniques to create an append-only, immutable, time-stamped chain of content. Copies of the blockchain are distributed on each participating node in the network".

Overall, five basic principles are underlying blockchain technology [14, 20, 22, 49]:

- **Distributed Ledger**—The entire ledger and its history are accessible by each using partner. No single user controls the data and its flow. Each partner on the ledger can verify the records directly.
- **Peer-to-Peer Transmission**—Communication happens among peers and in a decentralised way.
- **Transparency with Pseudonymity**—Every activity on the ledger is visible to anyone with access to the ledger.
- **Irreversibility of Records**—Once the records enter the distributed ledger/database, no one can change them because they link to every transaction record before them. All records are permanent and available to all users on the ledger.
- **Computational Logic**—The activities and transactions on the blockchain ledger are programmed to enable users to set up rules that automatically trigger transactions on the register.

Based on the above-focused blockchain technology principles, it is clear that this technology possesses some outstanding individual and collective benefits that make it unique and special, specifically for healthcare-related crises where clarity, consistency, efficiency, trust and integrity are vital. For instance, blockchain can prevent data loss and record tampering. Furthermore, due to blockchain technology's architectural design, utilizing it can ensure data integrity and security. In addition, since blockchain records are 'time-stamped' and stored almost everywhere on the ledger, all activities and transactions can be easily reviewed by everyone on the network. Therefore, this makes blockchain-enabled platforms transparent, traceable, and suitable for auditing, fraud detection, and public services in standard and critical states [49, 60].

Further, blockchain can let systems be autonomous and free from any central governance [41]. In other words, blockchain technology can enable its users to maximize cost savings and efficiency by excluding any intermediary systems or third parties. Overall, blockchain enables users to create a secure data-sharing platform to share data freely, synchronize services efficiently, and enhance interoperability significantly in different situations [40]. And finally, due to the cryptographic nature of blockchain technology, the authenticity of the recorded data on the decentralised public network can be easily verified [49]. For verification, different consensus mechanisms and algorithms are used [37]. In this regards, the most well-known consensus algorithm is the Proof-of-Work (PoW) which ensures reliable authentication, enhanced transaction verification, diminished cost, and increased speed and accuracy [18].

Overall, blockchain technology can improve processing efficiency, create business opportunities, formulate regulation requirements, and effectively enhance information security and transparency [14].

Blockchain technology has moved way beyond its earlier buzzword status. Blockchain technology is suitable to verify, secure and share data; therefore it is ideal for managing multi-party, inter-organisational, and cross-border transactions [57]. Blockchain technology can increase efficiency and accuracy, lower costs and enable users to focus on further growth. [32] and [22] highlight that this technology—blockchain—has arrived in numerous industries and organisations and is used for various collaborative purposes and business process improvements [18].

Another example of blockchain technology's emerging application is for managing food supply. One of the critical challenges all supply chains face is the lack of accessible, consistent and accurate data, which becomes even more severe and essential when the focus is on food supply, where food safety and quality are crucial. By using blockchain solutions, we can be sure that the food supply chain is managed effectively and reliably.

Among blockchain technology's application adopters, healthcare-related stakeholders are the most important ones [8]. The Healthcare sector is among the most regulated industries globally as it is directly related to humans. In addition, within the healthcare sector, challenges such as data inconsistency, data privacy, data sharing and lack of transparency among key roles players, and patients' inability to know and manage their records remain critical and mainly under question [49].

The Healthcare industry benefits from blockchain technology's inherent capabilities (e.g. shifting the ownership of medical data to patients, integrating data security, enhancing data transfer efficiency, etc.) extensively [8]. Blockchain technology in the healthcare industry has improved the transparency and communication between patients and healthcare providers [55]; however, some improvements can still occur especially for healthcare crisis related situations. For instance, the trend of improvement for blockchain technology is expected to accelerate to help alleviate the delivery problem of medicine, especially during a healthcare-related crisis [18].

Mainly, healthcare stakeholders are patients, pharmaceutical firms, hospital systems and insurance providers. According to [52], blockchain-based solutions provide the following capabilities within the healthcare sector:

- Aggregate healthcare-related information across stakeholders in a shared and decentralised way within a decentralised ledger/repository;
- Track and trace healthcare-related information across healthcare sector's stakeholders via a shared and decentralised data ledger/repository;
- Reconcile and validate the accessible electronic health record (EHR) across different stakeholders in the healthcare services/products' delivery value chain;
- Manage the validity of the electronic health record and automate processes using smart contracts.

Blockchain-mediated solutions enable healthcare-related stakeholders to capture and share medical records with authorised stakeholders in a transparent way. In addition, such solutions also help the users to capture the custody trail of medical supply back to the pharmaceutical companies, provide patient-centred care through more organised systems and smart contracts and rest assured the validity and reliability of the data are obtained [52].

Since the early days of the recent pandemic in 2020, the use of blockchain technology by governments, for-profit and not-for-profit organisations to provide viable solutions to some different challenges and issues in various industries and sectors have accelerated. According to [57], (p. 2) "It has taken the COVID-19 pandemic to push through the obstacles to blockchain adoption. The virus has revealed the weaknesses in our supply chains, our inability to deploy resources where they are most needed to address the pandemic, and difficulties in capturing and sharing the data needed to make a rapid decision in managing it".

To obtain a clear understanding of how blockchain-enabled applications within the healthcare industry have supported the stakeholders to overcome such urgent and critical challenges, its best to learn about a few real-time use case examples from different countries with various focuses. As shown in Table 1, governments and organisations have made sure that they are focused on the available resources and are using their creativity and innovative ideas to utilise blockchain technology since the early days of the recent global outbreak. They also attempt to combine such facilities with other technologies and processes to achieve their higher-level objectives.

To gain an in-depth understanding and knowledge of blockchain technology's prospects and solutions for the healthcare industry, we also need to establish a clear understanding of the different types of blockchain platforms available in the industry due to the diversification of interest in blockchain applications.

Although blockchain-mediated applications and platforms are considered to be decentralised, in practice, three distinguished blockchain types—public, private and consortium- have been noticed, which do not mainly follow the 'decentralisation' aspect of the initially defined blockchain technology.

Table 1 Blockchain-enabled healthcare products and solutions use case examples

Blockchain-enabled solution provider	Place/country	Details
Tymlez	Netherlands	Tymlez is a distributed ledger technology firm. It is one of the 10 Dutch companies that launched the 'TechAgainst Corona' initiative to freely provide services and technologies to the Dutch Government to fight the recent outbreak
		Founded in 2016 by Michael Reh and Reinier van der Drift, Tymlez was listed on the Australian securities exchange, and in 2019 it released its Blockchain Solution Platform (TBSP)
		It brings transparency to the medical supply chain by preventing predatory value extraction (e.g. price extorting). It helps to model the medical goods ecosystem through a platform that matches supply and demand
Alipay health	China	Alipay focuses on introducing Blockchain-enabled solutions that enable users to share approved and validated tamper-free information (e.g. healthcare related data)
		Alipay shares epidemic-related materials over mobile apps to help Chinese citizens learn good prevention habits
		The Health Commission and Committee of Economic and Information technology of Zhejiang Province leads the project and uses Ant Blockchain to keep the information accurate to its origin
Chinese University of Hong Kong & ConsensSys	China & Hong Kong	The Chinese University of Hong Kong and ConsensSys launched the COVID-19 digital health passport (Medoxie Platform) by using blockchain technology
		Initially, healthcare professionals and academics in Hong Kong used the digital health passport, but it later became available for patients

(continued)

Table 1 (continued)

Blockchain-enabled solution provider	Place/country	Details
		This digital passport records COVID-19 test results, temperature checks and vaccinations
		The digital passport platform facilitates limited and consented access to a patient's health information while protecting personal data privacy
Rapid Medical Parts (RMP)	USA	Founded in March 2020 by James Allen Regonor, Rapid Medical parts Inc
		A trusted blockchain-enabled digital medical supply chain focused on producing, designing and engineering lifesaving medical parts
		VertiTX Corp created Rapid Medical Parts (RMP) to respond to the USA's urgent medical supply chain needs
		RMP signed a cooperative agreement in April 2020 with the US Department of Defence to develop a novel emergency ventilation solution for hospitals to increase capacity for COVID-19 patient care and prepare a potential second wave of cases
		RMP converts the sleep apnea machines into ventilators using the built blockchain-powered platform initially made to buy and sell traceable 3D printed parts and printing instructions
		RMP enables a decentralised manufacturing process where clients can order and print medical parts for their use where and when it's required
MiPasa	USA	MiPasa is an open data platform which was created by HACERA through partnership work

(continued)

Table 1 (continued)

Blockchain-enabled solution provider	Place/country	Details
		The objective of MiPasa is to efficiently detect COVID-19 carriers and infection hotspots around the globe
		It helps practitioners and public health officials access the data they require and conclude and recommend solutions that can help subdue the outbreak or support recovery
		Designed to enable the synthesis of data sources, address their inconsistencies, help identify errors or misreporting and seamlessly integrate credible new feeds
		MiPasa is working on a map of all those infected to pinpoint more precisely where isolations and quarantines need to happen
Everyware & Hedera Hashgraph	USA & UK	The National Health Services (NHS) in the United Kingdom is using tech developed by Everyware (from the UK) and Hedera Hashgraph (US blockchain organisation)
		The aim is to keep a tamper-proof digital record of vaccines and pick up any irregularities where necessary and required
		Everyware uses sensors to monitor requirements in real-time, and Hedera is a blockchain consortium backed by Google and IBM
Emerge	Canada & Honduras	Emerge is a blockchain startup based in Toronto (Emerge Inc.) which launched a public safety app (Civitas)
		Civitas app helps local authorities, most importantly in Latin American countries, verify if the patients have travel rights, even if they don't have access to patients' medical records

(continued)

Table 1 (continued)

Blockchain-enabled solution provider	Place/country	Details
		Civitas app associates individuals' government ID numbers with unique blockchain-supported records. It allows authorities to know if the individuals qualify for a permit to leave their homes during the outbreak or not
		The Civitas app supports the citizens by showing which days are safest for them to go out if they are experiencing coronavirus-like symptoms
		Civitas enables the governmental agencies to design and implement more accurate and real-time data about the distribution of infection

Source [1, 3, 11, 12, 21, 29, 47, 54, 57]

- **Public Blockchains**—They are permissionless and are fully decentralised. Anyone can join the network, read or write and participate in their consensus with a full right without prior permission. Public blockchains can be vulnerable to privacy issues and cyberattacks. In this regards, Ethereum is a very good example, being used in multiple industries and supporting the development and use of smart contracts [49, 59].
- **Private Blockchains**—They are permissioned, and their blockchain-enabled application users require to be authorised to join the network. In private blockchains, authorised users are known to the network and can read, write and validate transactions. The two good examples for permissioned blockchain platforms are Hyperledger Fabric and Ripple which were introduced by Linux Foundation and Ripple Labs Inc. (ibid).
- **Consortium Blockchains**—They are less likely to experience cyberattacks and sit between public and private blockchain. They are categorised as permissioned blockchain and are used by independent organisations sharing information with little or no trust. Consortium blockchains are centralised and have less privacy and security concerns and no severe cyberattacks as all parties benefit from the mutual security aspect within the network (ibid).

2 Benefits of Blockchain Technology in Healthcare Sector

To facilitate the understanding of blockchain technology's benefits within the healthcare sector, addressing them from two different perspectives—patients and organisations (e.g. hospitals, clinics, insurance providers, pharmaceutical companies, etc.)—will be helpful. In Table 2, four distinct attributes for patient-related and healthcare organisational-related benefits have been highlighted and discussed.

Due to the nature of the health-related data, the healthcare sector's stakeholders have mainly focused on permission-based blockchain platforms to ensure privacy is secured; however, this contrasts with the decentralisation principle of blockchain technology. Furthermore, within the healthcare sector's business environment, due to continuous disruptions (e.g. technological, political, legal, environmental, social and economic) and the importance of operating as a sustainable business within a competitive business environment, public blockchain platforms have not been accepted and adopted widely. Healthcare organisations are reluctant to adopt public blockchain platforms because mainly their financial state influences their interests in utilising technologies for their businesses.

3 Challenges of Blockchain Technology in Healthcare Sector

Although blockchain technology has supported the healthcare industry's stakeholders in numerous ways, with its several advantages (as discussed in Sect. 3); however, it is still in its early stages and is rapidly evolving. Today only some of the core elements that make a blockchain are being used while other attributes are rejected. In this line, several challenges require careful attention within the healthcare industry in general and during health-related crises in particular.

3.1 Governance Issues

Lack of governance regulations and guidelines can prevent users from implementing and using blockchain-enabled applications accurately and appropriately [7, 17]. For instance, blockchain technology's promise has always been providing and supporting "decentralised governance". Today's blockchain technology architecture is rarely decentralised, as was intended in the original blockchain design. In practice, many blockchain solutions available today are governed by a single company (private blockchain) or small group of companies (consortium blockchain), and only authorised users (permissioned) can join (centralised governance).

Table 2 Blockchain-enabled benefits in healthcare sectors

Types of benefits	Attributes	Description	Blockchain type/access	References
Patient-related benefits	Privacy, security and authorization enhancement	The security of patients' health information is enhanced by focusing on a decentralised peer-to-peer network, placing the patient at the centre of the network. Data breach can be minimized and user verification can take place	Private/permissioned	[5, 6, 10, 13, 23, 35, 50, 51, 55, 58]
	Health data tracking	Physicians can track patients' data efficiently and effectively using time-stamps linked to each record on the network	Private and consortium/permissioned	[5, 13, 53, 61]
	Health status updates	Physicians are enabled to monitor patients' conditions and, where needed, provide immediate support	Private and consortium/permissioned	[6, 10, 55]

(continued)

Table 2 (continued)

Types of benefits	Attributes	Description	Blockchain type/access	References
	Personalised healthcare support	The authorised users of the distributed ledger can share medical records for creating more personalised healthcare products and services for patients	Private and consortium/permissioned	[10, 30, 53]
		*This benefit is critical for vulnerable patients where they require specific attention and support		
Healthcare organisational-related benefits	Pharmaceutical and medical supply chain management	Relying on the traceability feature of blockchain, supply chain stakeholders can manage the supply chain (e.g. prevent the distribution of counterfeit drugs in the community)	Public and consortium/permissonless and permissioned (depending on situation)	[6, 27, 43, 44, 53, 55]

(continued)

Table 2 (continued)

Types of benefits	Attributes	Description	Blockchain type/access	References
	Health data exchange	Healthcare organisations can securely share patients' information with other stakeholders for healthcare-related support and services	Consortium/permissioned	[10, 13, 23, 27, 35, 44]
	Medical insurance data management	Healthcare organisations can store, backup and use immutable medical insurance data where required	Consortium/permissioned	[5, 10, 17, 27, 39, 39, 39, 39, 44, 44, 44, 44, 61, 61]
	Clinical trials management	Pharmaceutical companies and medical institutions can manage clinical trials efficiently and effectively	Consortium/permissioned	[6, 23, 27, 45]

According to [16], there are four business "currencies" produced in digital environments: data, contracts, access and technology. When one company or consortium of companies builds a centralised blockchain within the healthcare sector, that dominant company can own and govern the technology, capture and centralise the data, control who can access or not access the solution, and set the terms of the smart contracts. In this line, blockchain-mediated applications' security is linked and interrelated with the authorisation aspect [5, 10, 33, 35, 44, 46, 53]. Overall, if the decentralisation factor fails to be implemented, we will always return to the problems of power and trust among stakeholders/users [19].

3.2 Scalability and Storage Capacity Concerns

Although blockchain technology is maturing, its issues related to the management and processing of high volume transactions per second are still unresolved [10]. According to [22], the storage of medical data on the blockchain network causes confidentiality and scalability issues. For instance, the storage of data on the blockchain makes it visible to everyone on the ledger because of the transparency and decentralised nature of the blockchain technology, which puts privacy at risk.

To use blockchain to help build a better future for the healthcare industry where managing health-related crises can be achievable, leaders must protect data privacy, be transparent about data usage, and avoid eroding democratic values with communities [57]. Furthermore, collecting and recording different medical records on a blockchain network can cause a significant storage issue. According to [24] and [48] the scalability constraint is linked to the computer power required to handle the high volume of transactions which needs careful attention and a better solution to overcome such challenge.

3.3 Lack of Technical Competencies Among Healthcare Personnel

According to [32], blockchain is based on machine language and non-technical medical employees may find hard to understand it. Given the unique aspects of blockchain-based collaboration; healthcare organisations need to develop different sets of capabilities among their staff to understand blockchain's benefits fully.

Smooth coordination between different organisational teams and technicians will be critical for adopting and implementing blockchain [5]. Overall, the biggest challenge in adopting this technology is not the technology itself, instead, it's the users' and stakeholders' change attitude for building a framework for collaboration across vendors, sectors and users [52].

3.4 Universal Interoperability and Standardization Issues

As blockchain is still evolving, the interoperability feature is becoming more and more vital for users [6, 10, 24, 28, 61] and still no established standards are available for it yet. Furthermore, blockchain implementation in the healthcare sector also is taking more time and effort to adopt due to the need for international certified standardisation.

Once an international standard is formatted and defined, the adoption of blockchain will become easier for stakeholders and they will be able to adapt their current available operations and systems with the blockchain-enabled platform and application [24, 28]. Overall, as more countries and healthcare stakeholders start to adopt blockchain-enabled applications and solutions, the issue of standardisation and universal interoperability will become eminent [42].

3.5 High Installation Costs, Slow Processing Speed and High Energy Consumption

Overall, utilising blockchain-enabled platforms can be time-consuming for healthcare stakeholders [2] and most importantly, its initial instalment can also be high [17, 53, 55, 62]. However, using blockchain can lower costs and support healthcare organisations to invest in other areas in the long run financially. Slow processing speed and high energy consumption occur because many users join the network [5, 13, 24, 33, 44, 58, 62].

4 Mapping Blockchain Technology Prospects and Solutions in the Healthcare Industry

There is a nexus between blockchain-related benefits and challenges that can help and support practitioners to focus on improving and developing more reliable healthcare-related products/services and processes. In this line, all stakeholders, whether governments, policymakers, leaders, practitioners, scholars and users, must be open and ready to move on and transform challenges into opportunities and be focused on optimised solutions available by blockchain technology to support societies during crises.

Based on the basic principles of blockchain technology and the identified patient and organisational benefits of blockchain-enabled applications in the healthcare industry, seven prospects are mapped for more promising healthcare-related products and services during normal and critical times.

4.1 Improve Scalability

One way to scale blockchain-enabled applications and solutions in the Healthcare sector is through the combination of network effects, learning effects and coordination effects [9]. This means that the more stakeholders become part of the blockchain-supported community (network effects), the value of the blockchain-enabled portal/platform will increase (learning effects) because of network effects, and in this line, stakeholders start creating value to one another (coordination effects). One of the risks in this area is the stakeholders' ability to adapt to the new situation and operating environment.

4.2 Track and Trace Medication and Medical Equipment

According to [22], counterfeit medications and medical equipment can cause serious health issues within societies, whether under normal situations or during healthcare-related crises such as pandemics. By using blockchain technology, pharmaceutical companies and medical equipment makers can focus on decentralised tracking systems that can ensure the traceability of medication and medical equipment in real-time. Pharmaceutical companies and medical device manufacturers can rely on the timestamp nature of the blockchain transactions and ensure that tracking will take place transparently and accurately [25, 45]. For example, MediLedger is working on applying blockchain technology to track and trace where a box of a drug is and where it has been at any time within the value chain. With blockchain-enabled applications, this process can be done without revealing confidential information to anyone in the ecosystem and being sure the right information is acquired.

4.3 Transform, Simplify and Streamline Partnerships

Collaboration is vital for humans in their personal and professional lives. Within the healthcare sector, to build successful products, services, and processes, leaders and managers need to work closely and collaborate with their inter-organisational and intra-organisational partners and stakeholders efficiently and effectively. For this to happen, commitment should be motivated, communication and information sharing should be enhanced, and information consistency should be considered [32].

Blockchain supports the creation and development of publicly monitored and governed digital ledgers where control and governance are shared (in general), and everything is transparently communicated; therefore, it can enhance the trust factor for further continuous successful partnerships and the development of new collaborations. According to [32], transparency and enhanced trust result from the technical design and the unique nature of blockchain that makes it impossible for anyone to change the contents of the distributed ledger without approval from other users.

Reference [32] discuss how blockchain technology fundamentally can alter each phase of collaboration. For instance, for the ‘partner selection’ phase, as blockchain share data on the network and smart contracts automatically ensure the execution of the confirmed agreements, the level of dishonesty and distrust will be minimised as no party will be willing to refrain from any future agreements that blockchain governs.

Furthermore, in the ‘agreement formation’ phase, due to the immutability nature of the blockchain technology, users will require to be more cautious when negotiating agreements as defined protocols and agreements cannot be easily changed, and everyone will be kept accountable. The immutability feature of blockchain technology supports the trust factor and supports more reliable and well-thought deals.

Finally, within the ‘execution’ phase, as blockchain technology reinforces the execution of the confirmed agreement, the process is managed efficiently and with consistency. The level of trust among collaborators increases, and they become more responsive and active during the execution phase as the information and data are confirmed in real-time. According to [56], (p. 5) “combining complementary capabilities from multiple organisations save time and other resources”. By collaborating on an industry level, companies can also split the costs and reduce the risks of innovation.

4.4 Transform Electronic Health Records (EHR) Management

One of the significant challenges healthcare systems are confronted with; especially during outbreaks, is about how in real-time they can share more medical data with more stakeholders for more purposes, while data integrity, security, patient privacy is ensured [20].

Unfortunately, in today’s technology disrupted, fast-paced business environment, there are still healthcare institutions and organisations that are manually attempting to reconcile medical and health-related data for their daily tasking. In such situations, scattered data sources are created, and it’s not clear where and when the data was recorded and who was responsible for recording the data. For instance, a medical doctor might know what medication was prescribed to a patient at his clinic; however, he may not be able to confirm whether the patient is still taking the medication or has visited another specialist and is taking other medications (ibid).

To overcome such challenges, it is advised to use blockchain-enabled platforms for streamlining and connecting all the dots. For example, by using a decentralised blockchain-enabled platform, all information about the patients’ medication, challenges, and conditions can be recorded securely on an open-source ledger where transparency is provided when additions and subtractions to the records are made. In this case, EHR data from all databases will be available through the blockchain-enabled ledger and transparency, data integrity and trust in the accuracy and reliability of the data will be maximised, and there will be minimum manual human intervention [20]. Such a platform also inherently includes an audit trail. Furthermore, such initiative also supports the patients' privacy rights and supports all parties' interests with no exclusivity. For instance, the blockchain-enabled platform for EHR records stores a signature of the EHR and notifies the patient who own the record/data. The signature assures that an unchanged copy of the medical record is obtained.

4.5 Transform Medical Supply Logistics

With technology advancement and digitisation, all business models across many industries are disrupted. For instance, no longer only two key parties are present in the collaboration equation. These days, technology-enabled platforms connect more stakeholders and create hubs for more expanded collaborations [9]. In this line, if medical supply logistics stakeholders endeavour to implement and develop a blockchain-enabled collaboration platform, they will enable multiple key role players to collaborate and co-govern their shared data at a single point of truth and rest assured that transparency is maximised. Furthermore, smart contracts can also be executed automatically on the blockchain-enabled ledger, which can minimise human interventions and document loss and enhance accuracy by holding all actor on the distributed ledger accountable to high standards.

A high level of transparency enables decision making optimisation throughout the medical supply value chain. Furthermore, blockchain technology can enhance quality assurance by managing permissions, ownership and accountability. This improves stakeholders' trust as it holds each member accountable for their conduct at every stage of the Medical Supply Value Chain (ibid).

4.6 Fix Healthcare Supply Chain Vulnerabilities

Using blockchain-enabled supply chain platforms, stakeholders can work collaboratively on a shared permanent decentralised ledger without being concerned about giving up control. All data will be collected using smart contracts and will be used in the decision-making process [18]. As the gathered data are in a cumulative blockchain sequence, no omissions, redundancies, or inaccuracies exist; therefore, it's reliable to reduce friction, expose fraud, and assure product authenticity with new speed [18, 34] as it is vital during healthcare-related crises such as pandemics.

4.7 Real-Time Update Through Intelligent Monitoring Systems

During healthcare-related crises, monitoring the situation—individual and society—and providing real-time updates is essential. Such initiative can be facilitated via the development and implementation of intelligent monitoring systems. For instance, installing a smart monitoring system on a wearable provides updates about the individual's health-related conditions (e.g. blood pressure, temperature, location, etc.) to the patient and the physician.

Furthermore, it can support the individual with sharing information about the community's state (e.g. high-density populated suburbs, news feeds, etc.). In this line, by leveraging the advantages of blockchain (e.g. data immutability, data integrity, etc.), the reliability of such intelligent monitoring systems can be reviewed and assured [4, 36, 38].

5 Summary and Conclusion

This chapter reviewed the fundamental aspects of blockchain technology in general and its applications within the healthcare industry. It discussed the benefits of such technology-mediated applications from both organisational and individual perspectives and developed a clear understanding of the nature of the blockchain-enabled solutions. It was clarified that the development of blockchain technology in the healthcare industry has its advantages and disadvantages, and blockchain can be compared to a General Purpose Technology (GPT) as it is pervasive and can be adopted by most sectors and industries. Blockchain technology can revamp global healthcare systems, especially in crises such as improving and developing the current and new healthcare-related products/services and processes. The chapter concluded seven prospects and solutions—scalability enhancement, medical product traceability, medical supply logistics improvement, healthcare supply chain and partnership optimisation, and real-time updates—that can support societies to overcome challenges promptly. Overall, blockchain-related attributes could boost hope and confidence in communities and support inventors, entrepreneurs, practitioners, and leaders with their daily healthcare-focused responsibilities and decision-making activities within and outside country borders.

References

1. Alizila. In: ALIBABA (ed.) Alipay Health Plan Aiming for 300M Users (2019)
2. Alonso, S.G., Arambarri, J., Lopez-Coronado, M., De La Torre Diez, I.: Proposing new blockchain challenges in eHealth. J. Med. Syst. **43** (2019)

3. Ang, A. In: MOBILEHEALTHNEWS (ed.) Medoxie COVID-19 Digital Health Passport (2021)
4. Bak, S., Pyo, Y., Jeong, J. Protection of EEG data using Blockchain platform. In: 7th International Winter Conference on Brain-Computer Interface (BCI). IEEE, Gangwon, Korea (2019)
5. Beinke, J.H., Fitte, C., Teutberg, F.: Towards a stakeholder-oriented Blockchain-based architecture for electronic health records: design science research study. J. Med. Internet Res. **21**, e13585 (2019)
6. Boulos, M.N.K., Wilson, J.T., Caluson, K.A.: Geospatial Blockchain: promises, challenges, and scenarios in health and healthcare. Int. J. Health Geogr. **17**, 25 (2018)
7. Cao, S., Hang, G., Liu, P., Hang, X., Neri, F.: Cloud-assisted secure eHealth systems for tamper-proofing EHR via blockchain. Inf. Sci. **485**, 427–440 (2019)
8. Chen, M., Malook, T., Rehman, A.U., Muhammad, Y., Alshehri, M.D., Akbar, A., Bilal, M., Khan, M.A. Blockchain-enabled healthcare system for detection of diabetes. J. Inf. Secur. Appl. **58** (2021)
9. Choudary, S.P., Van Anstyne, M.W., Parker, G.G.: Platforms and Blockchain Will Transform Logistics. Harvard Business Review. Havard Business Publishing, Brighton, Massachusetts (2019)
10. Clim, A., Zota, R.D., Constantinescu, R.: Data exchanges based on blockchain in m-Health applications. Procedia Comput. Sci. **160**, 281–288 (2019)
11. Cnbc In: BROWNE, R. (ed.) UK Hospital are Using Blockchain to Track the Temperature of Coronavirus Vaccines (2021)
12. Cuen, L. In: COINDESK (ed.) As Governments Rush to Track Coronavirus, Honduras May Offer a Privacy-First Model (2020)
13. Esmaeilzadeh, P., Mirzaei, T.: The potential of blockchain technology for health information exchange: experimental study from patients' perspectives. J. Med. Internet Res. **21**, e14184 (2019)
14. Farouk, A., Alahmadi, A., Ghose, S., Mashatan, A.: Blockchain platform for industrial healthcare: vision and future. Comput. Commun. **154**, 223–235 (2020)
15. Fernández-Caramés, T.M., Fraga-Lamas, P.: A review on the use of blockchain for the internet of things. IEEE Access **6** (2018)
16. Furlonger, D., Uzureau, C.: The 5 Kinds of Blockchina Project (and Which to Watch Out for). *Harvard Business Review.* Harvard Business Publishing, Brighton, United States (2019)
17. Gokalp, E., Gokalp, M.O., Coban, S., Eren, P.E.: Analysing opportunities and challenges of integrated Blockchain Technologies in healthcare. Lecture Notes in Business Information Processing. Springer Link (2018)
18. Grief, T., Nikbakht, E.: Review of Blockchain and emerging applications. In: Baker, H. K., Nikbakht, E., Smith, S.S. (Eds.) The Emerald Handbook of Blockchain for Business. Emerald Publishing Limited, Bingley, United Kingdom (2021)
19. Halaburda, H., Mueller-Bloch, C.: Will We Realize Blockchain's Promise of Decentralization? *Harvard Business Review*. Havard Business Publishing, Brighton, United States (2019)
20. Halamka, J.D., Lippman, A., Ekblaw, A.: The Potential for Blockchain to Transform Electronic Health Records. *Harvard Business Review*. Harvard Business Publishing, Brighton, United States (2017)
21. Hashgraph, H. In: Hashgraph, H. (Ed.) Everyware and Hedera Hashgraph Enabling Cold chain Monitoring of COVID-19 Vaccine for NHS Facilitiess (2021)
22. Hussien, H.M., Yasin, S.M., Udzir, N.I., Ninggal, M.I.H., Salman, S.: Blockchain Technology in the healthcare industry: trends and opportunities. J. Ind. Inf. Integr. **22** (2021)
23. Hylock, R.H., Zeng, X.: A Blockchain framework for ptient-centered health records and exchange (HealthChain): evaluation and proof-of-concept study. J. Med. Internet Res. **21**, e13592 (2019)
24. Kassab, M.H., Defranco, J., Malas, T., Laplante, P., Destefanis, G., Graciano, V.V.: Exploринng research in Blockchain for healthcare and a roadmap for the future. IEEE Trans. Emerg. Top. Comput. (2019)

25. Kaur, H., Alam, M.A., Jameel, R., Mourya, A.K., Chang, V.: A proposed solution and future direction for Blockchain-based heterogeneous medicare data in cloud environment. J. Med. Syst. **42**, 156 (2018)
26. Khan, A.M., Salah, K.: IoT security: review, blockchain solutions, and open challenges. Futur. Gener. Comput. Syst. **82**, 395–411 (2018)
27. Kumar, T., Ramani, V., Ahmad, I., Braeken, A., Harjula, E., Ylianttila, M. Blockchain utilization in healthcare: key requirements and challenges. IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom). Ostrava, Cech Republic (2018)
28. Kuo, T.T., Gabriel, R.A., Machado, L.O.: Fair compute loads enabled by Blockchain: sharing models by alternating client and server roles. J. Am. Med. Inform. Assoc. **26**, 392–403 (2019)
29. Insights, L. In: INSIGHTS, L. (ed.) Ant's Alipay Uses Blockchain to Process Health Insurance Claims in Seconds (2018)
30. Leeming, G., Cunningham, J., Ainsworth, J.A.: Ledger of me: Personalizing healthcare using Blockchain Technology. Front. Med. **6** (2019)
31. Li, X., Jiang, P., Chen, T., Luo, X., Wen, Q.: A survey on the security of Blockchain systems. Futur. Gener. Comput. Syst. **107**, 841–853 (2020)
32. Lumineau, F., Wang, W., Schilke, O., Huang, L.: How Blockchain Can Simplify Partnerships. *Harvard Business Review*. Harvard Business Publishing, Brighton, United States (2021)
33. Maesa, D.D.F., Mori, P.: Blockchain 3.0 applications survey. J. Parallel Distrib. Comput. **138**, 99–114 (2020)
34. Mccauley, A.: Why Big Pharma is Betting on Blockchain. Harvard Business Review. Harvard Business Publishing, Brighton, Massachusetts (2020)
35. Mcghin, T., Choo, K.-K.R., Liu, C.Z., He, D.: Blockchain in healthcare applications: research challenges and opportunities. J. Netw. Comput. Appl. **135**, 62–75 (2019)
36. Meng, W., Li, W., Hu, L.: Enhancing medical smartphone networks via Blockchain-based trust management against insider attacks. IEEE Trans. Eng. Manage. **64**, 1377–1386 (2020)
37. Mingxiao, D., Xiaofeng, M., Zhe, Z., Xiangwei, W., Qijun, C.: A review on consensus algorithm of Blockchain. In: 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, Banff, Canada (2017)
38. Mohsin, A.H., Zaidan, A.A., Zaidan, B.B., Albahri, O.S., Albahi, A.S., Alsalem, M.A., Mohammed, K.I.: Blockchain authentication of network applications: taxonomy, classification, capabilities, open challenges, motivations, recommendations an future directions. Comput. Stand. Interfaces **64**, 41–60 (2019)
39. Monrat, A.A., Schelen, O., Anderson, K.: A survey of Blockchain from the perspectives of applications, challenges, and opportunities. IEEE Access **7**, 117134–117151 (2019)
40. Narayanan, A., Clark, J.: Bitcoin's academic pedigree. Commun. ACM **60**, 36–45 (2017)
41. Nofer, M., Gomber, P., Hin, O., Schiereck, D.: Blockchain. Bus. Inf. Syst. Eng. **59**, 183–187 (2017)
42. Olnes, S., Ubacht, J., Hjanssen, M.: Blockchain in government: benefits and implications of distributed ledger technology for information sharing. Gov. Inf. Q. **34**, 355–364 (2017)
43. Onik, M.M.H., Aich, S., Yang, J., Kim, C.S., Kim, H.C.: Chapter 8—Blockchain in Healthcare: Challenges and Solutions. Academic Press, Big Data Analytics for Intelligent Healthcare Management (2019)
44. Pandey, P., Litoriya, R.: Implementing healthcare services on a large scale: challenges and remedies based on Blockchain Technology. Health Policy Technol. **9**, 69–78 (2020)
45. Pandey, P., Litoriya, R.: Securing e-health networks from counterfeit medicine penetration using Blockchain. Wirel. Pers. Commun. 1–19 (2020b)
46. Prokofieva, M., Miah, S.: Blockchain in healthcare. Australas. J. Inf. Syst. **23** (2019)
47. Regonor, J.A.: Trust, compassion, here to fight [Online]. Rapid Med. Parts (2021)
48. Roehrs, A., Da Costa, C.A., Da Rosa Righi, R.: OmniPHR: a distributed architecture model to integrate personal health records. J. Biomed. Inform. **71**, 70–81 (2017)
49. Sanka, A.I., Irfan, M., Huang, I., Cheung, R.C.C.: A survey of breakthrough in Blockchain technology: adoptions, applications, challenges and future research. Comput. Commun. **169**, 179–201 (2021)

50. Shah, B., Shah, N., Shakhla, S., Sawant, V.: Remodeling the healthcare industry by employing Blockchain Technology. International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET). IEEE, Kottayam, India (2018)
51. Shahnaz, A., Qamar, U., Khalid, A.: Using Blockchain for electronic health records. IEEE Access **7**, 147782–147795 (2019)
52. Sharma, L., Olson, J., Guha, A., Mcdouogal, L.: How Blockchain will transform the healthcare ecosystem. Bus. Horiz.sS (2021)
53. Shuaib, K., Saleous, H., Shuaib, K., Aki, N.: Blockchains for secure digitized medicine. J. Pers. Med. **9**, 35 (2019)
54. Singh, G., Levi, J. In: IBM (ed.) MiPasa Project and IBM Blockchain Team on Open Data Platform to Suport COVID-19 Response (2020)
55. Tanwar, S., Parekh, K., Evans, R.: Blockchain-based electronic healthcare record system for Healthcare 4.0 applications. J. Inform. **50** (2020)
56. Tapscott, D., Vargas, R.V.: Blockchain is Changing How Companies Can Engage With Customers. *Harvard Business Review*. Havard Business Publishing, Brighton, Massachusetts (2021)
57. Van Hoek, R., Lacity, M.: How the pandemic is pushing blockchain forward. Harvard Business Review. Harvard Business Publishing, Brighton, Massachusetts (2020)
58. Vora, J., Nayyar, A., Tanwar, S., Tyagi, S., Kumar, N., Obaidat, M.S., Rodrigues, J.J.P.C.: BHEEM: A Blockchain-based framework for securing electronic health records. IEEE Globecom Workshops (GC Wkshps). United Arab Emirates, Abu Dhabi (2018)
59. Vranken, H.: Sustainability of bitcoin and Blockchains. Curr. Opin. Environ. Sustain. **28**, 1–9 (2017)
60. Yang, L.: The blockchain: state-of-the-art and research challenges. J. Ind. Inf. Integr. **15**, 80–90 (2019)
61. Zhang, P., Schmidt, D.C., White, J., Lenz, G.: Chapter one - blockchain technology use cases in healthcare. Adv. Comput. **111**, 1–41 (2018)
62. Zheng, X., Sun, S., Mukkamala, R.R., Vatrapu, R., Ordieres-Mere, J.: Accelerating health data sharing: a solution based on the internet of things and distributed ledger technologies. J. Med. Internet Res. **21**, e13583 (2019)

Future Directions and Roadmaps

The Role of Healthcare in Post Pandemic Era—"COVID Normal"

Tej Prakash Sinha, Brunda RL, Sakshi Yadav, Vishakh C. Keri, and Sanjeev Bhoi

Abstract COVID-19 pandemic created a havoc and hampered every sphere of life. Healthcare industry has been majorly affected. Post pandemic era requires adaptation and modifications to combat the damage caused by the pandemic. It also demands preparedness for management of future infectious pandemics. Pandemic management plan and a pandemic management team are the need of the hour. Digitalization of healthcare industry and increased utility of telehealth services could be sustained changes extending into the post pandemic phase.

Keywords COVID normal · Pandemic management · Future infectious pandemics · Telehealth

1 Introduction

The effects of the COVID-19 pandemic are striking as it has affected greatly the social, political, economic, and healthcare aspects globally. The COVID-19 has taken a toll over the world and its end anytime soon appears to be a bleak possibility. This pandemic accelerated the implementation and adoption of numerous changes in public health interventions.

COVID-19 did not create new problems but violently brought to the surface many of the challenges healthcare systems have been facing for a long time. Beyond the health and human tragedy of the coronavirus, it is now widely recognized that the pandemic triggered the most serious economic crisis in a century.

Rapid implementation of social distancing measures and rescheduling of elective procedures has led healthcare providers to resort to digital health applications to

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(at least partially) grant access to virtual consultations and remote visits and monitoring [1]. As a result, in just three months, there has been an unparalleled surge in digital health adoption, with a general scale-up of telemedicine and an up to ten-fold increase in the number of online consultations reported in the United States [2, 3]. However, if not managed properly, digitalization can also widen inequalities between patients, since it requires digital and internet access that involve not only suitable devices, but also basic IT skills. While the economic incentives can be set by specific governmental programs, there are many barriers to internet access, such as age and education [4].

The 'infodemic' of false information about COVID-19 is exacerbating the fear of contagion, misconceptions and myths about the virus which has led the health care providers to be seen as a risk to communities rather than the solution to this public health emergency.

The comforting prospect for the post-COVID-19 era is the realization that a substantial portion of healthcare activities in the wider sense can be improved by technologically empowered approaches, and some can even be done remotely equally as effectively. Advanced telehealthcare innovations will be continually utilized in the post pandemic phase too. It has been observed that in recent times, telehealth utility has increased by 38 times from pre-covid baseline. Positive attitude towards digital healthcare has been showcased by both consumers and providers. Investment in virtual healthcare industry has also increased by three times as compared to 2017 [5].

Though post pandemic era seems similar to times before world was affected by COVID-19, in reality COVID-19 has left an everlasting mark in many sectors. Like already discussed, digitalized healthcare is just one of the few examples of such pandemic impact. Lessons learnt during the pandemic necessitate a need for better, well planned interventions, management strategies and preparedness for future pandemics. With anticipated third wave of surge in COVID-19, formulation of an institutional pandemic management plan (PMP) and concentration on capacity building measures still remains main focus in immediate post pandemic era too.

2 Problem Statement

Infectious diseases should be considered amongst the most important health hazards that we will need to continue facing in the foreseeable future as we have been hit with numerous pandemics, including H1N1, Ebola, SARS-CoV, MERS-CoV, and currently, COVID-19 in past few decades. Thus, the transformation of various health services at the individual as well as the societal and governmental levels seems bound to happen.

This pandemic proved many aspects of healthcare, a failure, especially in terms of their overall readiness. Even after contingency plans were already in place, healthcare systems appeared unable to absorb and manage sudden and persistent pressures on their workload especially in the settings of acute care. Staff shortages may be the primary challenge to implementing surge capacity plans during a pandemic. Staff may be furloughed due to unprotected exposures or illness. COVID-19 has sickened many health care workers, although it is unclear how many of these were personal protective equipment (PPE) device failures versus failure to use PPE for patients with mild or atypical symptoms [6].

During the pandemic, the tele-health services has been widely utilized and hence there is a high chance that significant portion of health services will remain tele-health based post covid. Apart from its numerous advantages, it may act like a double edged sword sometimes. Virtual clinical treatment decreases human interaction among the healthcare professionals and patients that increases the risk of error in clinical services, if the service is delivered by inexperienced professional. Moreover, confidential medical information can be leaked through faulty electronic system. It might take longer time for the difficulties in connecting virtual communication due to low internet speed or server problem. Other than that, it requires tough legal regulation to prevent unauthorized and illegal service providers. Also many patients were unable to use digital services due to lack of knowledge or skills to use internet or other web devices. The pandemic has also highlighted that poor health literacy among the general population is an underestimated public health problem globally [7].

One of the defining aspects of the current pandemic was the unprecedented levels of misinformation, conspiracy theories, and rumors reproduced by lay and social media related to COVID-19; these can only be counterproductive in the fight against the current epidemic, both in the short and long term. Consistency in the public health messaging as well as increased funding dedicated to fact-checking seems to be needed as the immediate first step. Enormous quantities of COVID-19 information that seem continually to be expanding also places a significant burden on clinicians seeking to respond to patient questions and, when appropriate, modify treatment recommendations [8].

COVID-19 has exposed health workers and their families to high level of risk. Although not representative, data from many countries across WHO regions indicate that COVID-19 infections among health workers are far greater than those in the general population. In addition to physical risks, the pandemic has placed extraordinary levels of psychological stress on health workers. Extrinsic organizational risk factors—including increased work demands and little control over the work environment—and the trauma of caring for patients who are critically ill have been heightened by the COVID-19 pandemic and represent important exacerbating factors for poor mental health among health-care workers. Despite serving COVID patients and risking their life, healthcare workers are also facing violence in many countries. Under usual working conditions, severe burnout syndrome affects as many as 33% of critical care nurses and up to 45% of critical care physicians [9].

3 Post Pandemic Era: The "COVID Normal"

The key areas of emphasis during post pandemic era should be:

i. *Resumption of stalled services*—During COVID-19 pandemic routine healthcare services were stalled in most countries. During COVID-19 times most nations had set up separate covid patient care facilities which were disjunct from other parts of the hospital. Current day scenario where multiple waves of pandemic have been anticipated it would be wiser to adapt to certain models such as "Covid Capable Healthcare Services" where covid care is integrated with multispecialty care needed by patients thus focusing on a holistic approach [10].

ii. *Management of post covid squeal*—Covid-19 pandemic has led to major setbacks in health and economy sector. WHO estimates atleast 3 million excess deaths to be Covid-19 related [11]. Post-covid syndrome has been reported in about 10–50% of covid-19 infected population [12–14]. The post pandemic era thus should concentrate on handling damage caused by devastating pandemic in addition to challenges associated with resumption of normalcy.

iii. *Preparedness and prevention of further outbreaks*—With constantly mutating virus, detection of various new strains around the world, infectious Variants Of Concern (VOCs) and unclear evidence of vaccine efficacies against these VOCs, strict adherence to infection prevention measures should continue to be the focus of post pandemic normalcy [15].

iv. *Digital preparedness—"The digitally normal post-covid phase"*—Post-pandemic period will most likely resonate the impact of digitalization and technological interventions which occurred during the pandemic phase. Telehealth services, E-triage services, artificial intelligence in the form of chatbots, humanoid robots for triaging, disinfection, sample and food transport will mostly continue to prevail as important adjuncts to conventional patient care [16, 17].

4 Pandemic Management Plan—Need of the Hour

Covid-19 was declared a pandemic on 11th march 2020 by the Director General of World Health Organization (WHO) [18]. Timing of interventions to curtail pandemic spread is the key factor influencing outcomes. A theoretical model suggested if non-pharmacological interventions had been implemented 1 week, 2 weeks or 3 weeks earlier than actual implementation time in China, the number of cases could have been reduced by 66%, 85% or 95% respectively and if interventions were delayed by one week period the case load could have increased by three folds [19]. Similar delays with exponential rise in cases has been noted throughout the world. Main reason for these delayed responses could be due to lack of capacity building and preparedness in communities to combat emerging infectious diseases [20]. Infectious diseases have proven to be a global threat mandating strategic action plans. To address emerging infectious disease threats CDC has devised a strategic plan with four main goals of strict surveillance, applied research, prevention—control and infrastructural modifications [21]. Similar strategic plans need to be formulated at national and institutional levels for smoother operation during infectious pandemics. Pandemic situations unmask the demand—supply mismatch present in healthcare sectors. A strategic plan to combat these existent gaps in pre-pandemic phase could reduce chaos and prove to be a game changer. Institutional/Hospital Pandemic Management Plan (HPMP) is need of the hour to address current pandemic as well as unprecedented future infectious pandemics. PMP thus needs to be considered an integral part of pandemic phase as well as the post pandemic phase.

4.1 Proposed Pandemic Management Plan

Disaster has been defined as “an unusual natural or man-made event, including an event caused by failure of technological systems, which temporarily overwhelms the response capacity of human communities, groups of individuals or natural environments and which causes massive damage, economic loss, disruption, injury, and/or loss of life”. Epidemics have been included under biologic phenomenon category of natural disasters [22]. Disaster management cycle has been formulated to address pre-disaster preparedness, intra-disaster response and post-disaster recovery/rehabilitation. Applying these principles to cruise through pandemic scenarios appears appropriate (Fig. 1).

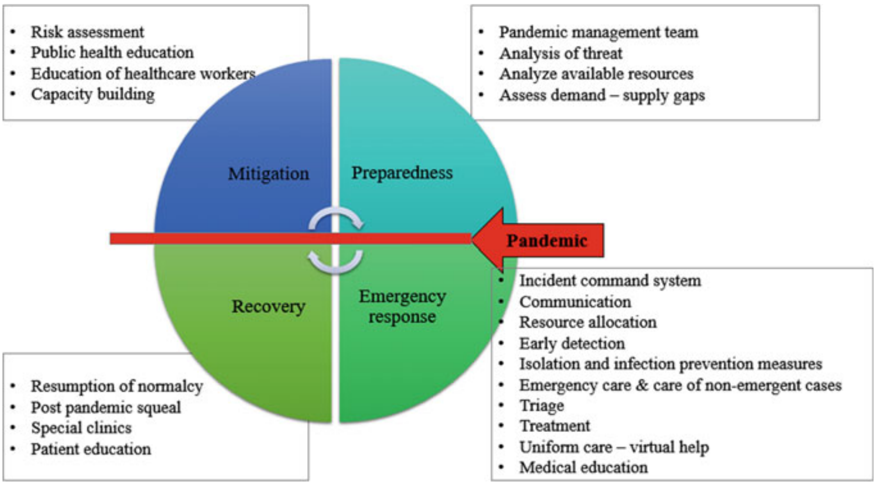

Fig. 1 Pandemic management cycle—four phases

4.2 Pandemic Management Cycle—Four Phases

1. *Mitigation*—Mitigation embraces all measures taken to reduce both the effects of the pandemic itself and the vulnerable conditions to it in order to reduce the scale of a future pandemic. Risk assessment, public health education, education of healthcare workers and capacity building constitute key elements of this phase. Virtual education models such as online classes or awareness programs to educate the general public could be beneficial. Virtual conferences or symposia for healthcare professional to update and equip them with preventive measures, latest guidelines to combat the pandemic will be helpful in uniform care during pandemic phase.
2. *Preparedness*

    a. Pandemic management team (PMT)—An institutional "pandemic management team" needs to be formed consisting of multidisciplinary personnel. Infectious diseases specialist, respiratory physicians, emergency physicians, staff from hospital administration, general physicians, pediatricians, nursing officers, sanitation workers, social workers and technical staff to facilitate virtual care for patients should all be a part of PMT. Pandemic management will be like an orchestral performance which requires every individual involved from various disciplines to be aware of their roles and responsibilities thoroughly. In a pandemic situation an intimation from incident command system should trigger immediate response from PMT without any chaos. This requires manpower training well in advance. Representatives from each field who are members of the PMT need to be further responsible for training individuals who will be recruited in the response activity. For example, representative from Infectious diseases will be responsible for hospital infection prevention and control. They need to train health care personnel or residents who will be working in the response teams during a pandemic in infection prevention strategies. They need to work in collaboration with respiratory therapists and hospital administration members to formulate isolation guidelines for infective patients, to earmark isolation areas of the hospital, to organize training sessions for residents to teach personal protective strategies etc. Similarly an emergency physician need to work in collaboration with general physician, respiratory physicians, hospital administration staff to build surge capacity and modify emergency rooms to cater to both sick infective and non-infective patients simultaneously while adhering to infection prevention measures. PMT needs to be formed and be functional with regular meetings and practice drills during pre-pandemic and post-pandemic phase too as this will help entire institute remain informed regarding available resources and shortcomings. Gaps present can be bridged beforehand and chaos can be reduced in pandemic phase.

b. Analysis of threat—Continuous strict surveillance is an integral part of pre-pandemic preparedness. Awareness regarding threat of resurgence of the pandemic in the society.
c. Analyze available resources—PMT formed should be aware of the resources available example oxygen cylinders, oxygen masks supplied regularly, mechanical ventilators if a respiratory illness is expected. Lack of essential resources needs to be noted and measures to avail adequate supplies to be undertaken in the pre-pandemic phase itself. In the recent Covid-19 pandemic world witnessed acute shortage of personal protective equipment and oxygen supply. Atleast some amount of disparity could be avoided during the second wave of pandemic but countries diligently failed resulting in suboptimal care to patients and increased exposure and risk of infection of HCW. Such events can be avoided and reduced if prior preparation and awareness can be instilled regarding available resources and plans be made to either increase supplies or to judiciously use available limited resources. Digital dashboards can be incorporated in all healthcare setups to keep a log and continuous audit of all essential commodities.
d. Assess demand—supply gaps—Pandemic exaggerates demand–supply mismatch. So preparedness regarding unmasking of such disparities even in a developed economy is extremely important. A knowledge of supply chain and regarding important vendors is necessary. And in cases of anticipated international travel/transport disruption, mobilization of local vendors who could cater to essential needs well in advance might be essential. This could prove beneficial and help bridge the demand–supply mismatch.

3. *Emergency response*

   a. Incident command system (ICS)—The roles for ICS system are to prepare the organization, its staff, patients, and city to deal with the pandemic in the best way possible. Objectives are carried out through 5 major functional areas: command, operations, planning, logistics, and finance/administration. The ICS helps focus leadership time and attention on those issues that mattered most [23].
   b. Communication—Clear, consistent communication intradepartmental, interdepartmental, with patients and general public are all important components to.
   c. Resource allocation—Resource assessment and allocation is a responsibility of the incident command system.
   d. Early detection—Once the pandemic strikes, first and foremost important step of management will be early detection of cases. This might include early warning signs, clinical scores to detect suspected infective patients and new testing methods to confirm diagnosis.
   e. Isolation and infection prevention measures—Infectious pandemics will require setting up isolation facilities quickly to contain spread. Negative pressure rooms, distancing amongst patients, limiting number of people in

a room, universal masking and hand hygiene are all important infection control measures to be adhered to.

f. Emergency care and care of non-emergent cases—in a pandemic scenario, overwhelmed healthcare systems usually shut down non-emergency and non-essential services. Chronically ill patients land up in already overburdened emergency departments due to lack of any other portal to address their issues. Virtual consultations or teleconsultations during pandemic can be helpful to prevent the above problem.
g. Triage—Triage facilities are the first point of medical contact for patients. Patients need to be categorized based on the severity of symptoms as routinely done and additionally need to be triaged based on probability of being infective too. Improper ineffective triage could aggravate disease spread and also lead to inadequate care. A two-step triage model has been proposed for triage of covid-19 patients at emergency department [24]. Electronic triage models have emerged as technologically driven solutions for triage during pandemic. Telehealthcare technology is both patient centred as well as physician centred. Integrating triage with virtual visits to create a broader front door for healthcare that enables patients to easily get care when they need it and lowers the cost of care by avoiding unnecessary ED visits [25].
h. Treatment—Treatment guidelines to handle the pandemic need to be formulated by the decision making team and uniformly followed throughout the institute.
i. Uniform care—virtual help—The standard of care could vary based on institutional limitations. Peripheral health care centers and remote hospitals catering to patients might need a helping hand from apex institutes or tertiary care centers. Tele-health based hub and spoke models could prove beneficial to bridge these knowledge gaps [26]. Higher levels of patient satisfaction due to reduced wait time, better instructions and technical details has been observed at few centers [27]. Strengthening tele-health model in pre-pandemic and post-pandemic phase is essential for its smooth functioning during pandemic phase.
j. Medical education—COVID-19 pandemic has disrupted the traditional structure of medical education. The new limitations of physical presence have accelerated the development of an online learning environment, comprising both of asynchronous and synchronous distance education, and the introduction of novel ways of student assessment. Online learning and simulation have become the new normal strategies of medical education [28].

4. *Recovery*

   a. Resumption of normalcy—Post pandemic phase comes with many challenges. Dealing with the damages caused by the pandemic, resumption to pre-Covid normalcy is necessary. Streamlining care of chronically ill patients, rescheduling work hours, restarting routine services are necessary but with a caution of possibility of another wave and need to switch to pandemic model immediately.

b. Post pandemic squeal—Patients might present with post-covid squeal such as lung fibrosis, thromboembolic phenomenon, myalgia, fatigue and other symptoms which require evaluation and treatment.
c. Special clinics—Special clinics or separate care facilities to cater to post-covid syndrome patients might ease burden on routine and emergency care facilities. Such measures would also ensure better care and follow up of this subset of patients.
d. Patient education—Patient education in the recovery phase regarding possible complications and alarming symptoms, awareness regarding immediate visit in case of any severe symptoms and need for covid appropriate behavior due to risk of reinfections and variants of concerns would be necessary. This would help instil caution and also stress on the importance of vaccination.
e. Digitalization of services—On-demand virtual urgent care can work as an alternative to lower acuity emergency department (ED) visits, urgent care visits, and after-hours consultations. These are the most common telehealth use cases today among patients. This allows them to remotely consult on demand with an unknown provider to address immediate concerns and avoid a trip to the ED. Virtual office visits with an established provider for consults that do not require physical exams or concurrent procedures enables clinicians to better manage patients with chronic conditions, with the support of remote patient monitoring, digital therapeutics, and digital coaching, in addition to virtual visits. The value of virtual care can be measured by quantifying clinical outcomes, access improvement, and patient/provider satisfaction [5].

Studies have shown that implementation of a national hospital disaster preparedness plan increased the hospital disaster preparedness score by almost 25% [29]. A pandemic management plan implementation can thus prove extremely beneficial for healthcare sectors in post-covid era to cope with damages caused by the pandemic as well as be well prepared to reduce negative impact of future pandemics.

Strategic management plans have been prepared for influenza pandemic and recently for global response of covid-19 pandemic too [30].

5 Conclusion

COVID-19 pandemic has had a waxing waning course. Healthcare systems have been devastated due to unforeseen case surges. Similar pandemics are anticipated in the future, considering which the post pandemic era health goals need to focus on a uniform "Pandemic Management Plan" formulation and implementation at institutional, national and international levels and also on strengthening virtual care models for use during pandemics. Regular meetings to discuss shortcomings in healthcare setups and to practice drills for pandemic management are necessary. Multidisciplinary, multisectoral management of pandemic is the need of the hour. Post pandemic era cannot forget to continue complying with COVID-19 appropriate behaviour considering variant strains causing disease. Health care setups need to continue to be vigilant and at the same allow smooth transition from pandemic phase to post pandemic COVID normal.

References

1. Greenhalgh, T., Wherton, J., Shaw, S., Morrison, C.: Video consultations for covid-19. BMJ **368**, m998 (2020). http://www.bmj.com/content/368/bmj.m998.abstract
2. Ohannessian, R., Duong, T.A., Odone, A.: Global telemedicine implementation and integration within health systems to fight the COVID-19 pandemic: a call to action. JMIR Public Health Surveill. **6**(2), e18810 (2020). https://publichealth.jmir.org/2020/2/e18810
3. Petracca, F., Ciani, O., Cucciniello, M., Tarricone, R.: Harnessing digital health technologies during and after the COVID-19 pandemic: context matters. J. Med. Internet Res. **22**(12), e21815 (2020). http://www.jmir.org/2020/12/e21815/
4. Tarricone, R., Cucciniello, M., Armeni, P., Petracca, F., Desouza, K.C., Hall, L.K., et al.: Mobile health divide between clinicians and patients in cancer care: results from a cross-sectional international survey. JMIR Mhealth Uhealth **7**(9), e13584 (2019). https://mhealth.jmir.org/2019/9/e13584/
5. Bestsennyy, O., Gilbert, G., Harris, A., Rost, J.: Telehealth: a quarter-trillion-dollar post-COVID-19 reality?. Mc Kinsey & Company - Healthcare systems and services. https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/telehealth-a-quarter-trillion-dollar-post-covid-19-reality (2021)
6. Hick, J.L., Hanfling, D., Wynia, M.K., Pavia, A.T.: Duty to plan: health care, crisis standards of care, and novel coronavirus SARS-CoV-2. NAM Perspectives Discussion Paper, National Academy of Medicine, Washington, DC (2020)
7. Mubaraki, A.A., Alrabie, A.D., Sibyani, A.K., Aljuaid, R.S., Bajaber, A.S., Mubaraki, M.A.: Advantages and disadvantages of telemedicine during the COVID-19 pandemic era among physicians in Taif, Saudi Arabia. Saudi Med. J. **42**(1), 110–115 (2021). https://pubmed.ncbi.nlm.nih.gov/33399180
8. Smith, G.D., Ng, F., Ho Cheung Li, W.: COVID-19: emerging compassion, courage and resilience in the face of misinformation and adversity. J. Clin. Nurs. **29**(9–10), 1425–1428 (2020). https://doi.org/10.1111/jocn.15231
9. Poncet, M.C., Toullic, P., Papazian, L., Kentish-Barnes, N., Timsit, J.-F., Pochard, F., et al.: Burnout syndrome in critical care nursing staff. Am. J. Respir. Crit. Care Med. **175**(7), 698–704 (2007). https://doi.org/10.1164/rccm.200606-806OC
10. Keri, V.C., Brunda, R.L., Jorwal, P., Sethi, P., Wig, N.: Decentralizing COVID-19 care—moving towards a COVID-19-capable healthcare system (CCHS). Int. J. Health Plan. Manag. (2021). https://doi.org/10.1002/hpm.3158
11. The impact of COVID-19 on global health goals. World Health Organization - WHO Newsroom. Spotlight (2021 May 20)
12. Pavli, A., Theodoridou, M., Maltezou, H.C.: Post-COVID syndrome: incidence, clinical spectrum, and challenges for primary healthcare professionals. Arch. Med. Res. (2021). https://www.sciencedirect.com/science/article/pii/S0188440921000813
13. Moreno-Pérez, O., Merino, E., Leon-Ramirez, J.-M., Andres, M., Ramos, J.M., Arenas-Jiménez, J., et al.: Post-acute COVID-19 syndrome. Incidence and risk factors: a Mediterranean

cohort study. J. Infect. **82**(3), 378–383 (2021). https://www.sciencedirect.com/science/article/pii/S0163445321000098
14. Bellan, M., Soddu, D., Balbo, P.E., Baricich, A., Zeppegno, P., Avanzi, G.C., et al.: Respiratory and psychophysical sequelae among patients with COVID-19 four months after hospital discharge. JAMA Netw. Open **4**(1), e2036142 (2021). https://doi.org/10.1001/jamanetworkopen.2020.36142
15. World Health Organization - Newsroom: The effect of virus variants on COVID-19 vaccines. https://www.who.int/news-room/feature-stories/detail/the-effects-of-virus-variants-on-covid-19-vaccines?
16. Brunda, R.L., Keri, V., Sinha, T., Bhoi, S.: Re-purposing humanoid robots for patient care in COVID-19 pandemic. Int. J. Health Plan. Manag. (2020)
17. Almalki, M., Azeez, F.: Health chatbots for fighting covid-19: a scoping review. Acta Inf. Med. **28**(4), 241–247 (2020). https://pubmed.ncbi.nlm.nih.gov/33627924
18. Timeline: WHO's COVID-19 response. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline#event-71
19. Lai, S., Ruktanonchai, N.W., Zhou, L., Prosper, O., Luo, W., Floyd, J.R., et al.: Effect of non-pharmaceutical interventions to contain COVID-19 in China. Nature **585**(7825), 410–413 (2020). https://doi.org/10.1038/s41586-020-2293-x
20. Gostin, L.O., Wiley, L.F.: Governmental public health powers during the COVID-19 pandemic: stay-at-home orders, business closures, and travel restrictions. JAMA **323**(21), 2137–2138 (2020). https://doi.org/10.1001/jama.2020.5460
21. Binder, S., Levitt, A.M., Hughes, J.M.: Preventing emerging infectious diseases as we enter the 21st century: CDC's strategy. Public Health Rep. **114**(2), 130–134 (1999). https://pubmed.ncbi.nlm.nih.gov/10199715
22. Mohamed, S.I.: Disaster types. Disaster Prev. Manag.: Int. J. **16**(5), 704–717 (2007). https://doi.org/10.1108/09653560710837019
23. Cook, J.: Incident command in the time of COVID-19. Lab. Med. **51**(6), e78–e82 (2020). https://pubmed.ncbi.nlm.nih.gov/32909043
24. Mathew, R., Sinha, T., Sahu, A., Bhoi, S., Galwankar, S.: Coronavirus-19 pandemic: a two-step triage protocol for emergency department. J. Emerg., Trauma, Shock **13**, 169–171 (2020). https://www.onlinejets.org/article.asp?issn=0974-2700;year=2020;volume=13;issue=2;spage=169;epage=171;aulast=Mathew
25. Alhaidari, F., Almuhaideb, A., Alsunaidi, S., Ibrahim, N., Aslam, N., Khan, I.U., et al.: E-Triage systems for COVID-19 outbreak: review and recommendations. Sensors **21**(8), (2021)
26. Keri, V.C., Brunda, R.L., Sinha, T.P., Wig, N., Bhoi, S.: Tele-healthcare to combat COVID-19 pandemic in developing countries: a proposed single centre and integrated national level model. Int. J. Health Plan. Manag. (2020). https://doi.org/10.1002/hpm.3036
27. Luna, P., Lee, M., DeLucia, N., London, Y., Hoffman, P., Burg, M., et al.: Telehealth care before and during COVID-19: trends and quality in a large health system. J. Am. Coll. Cardiol. **77**(18_Suppl._1), 3229 (2021). https://doi.org/10.1016/S0735-1097(21)04583-6
28. Papapanou, M., Routsi, E., Tsamakis, K., Fotis, L., Marinos, G., Lidoriki, I., et al.: Medical education challenges and innovations during COVID-19 pandemic. Postgrad. Med. J. (2021). http://pmj.bmj.com/content/early/2021/03/28/postgradmedj-2021-140032.abstract
29. Beyramijam, M., Rasouli-Ghahfarokhi, S.M., Fathollahzadeh, A., Rahimzadeh, A., Shahabirabori, M.A., Aminizadeh, M.: The effect of education and implementation of "National Hospital Disaster Preparedness Plan" on an Iranian hospital preparedness: an interventional study. J. Educ. Health Promot. **8**, 215 (2019). https://pubmed.ncbi.nlm.nih.gov/31867379
30. World Health Organization - Strategy and planning: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/strategies-and-plans

Scenario Assessment for COVID-19 Outbreak in Iran: A Hybrid Simulation–Optimization Model for Healthcare Capacity Allocation

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Abstract Today, all countries globally, including Iran, face the challenge of spreading the COVID-19 disease. Given the limited capacity of the health care system and the risk of a recurrence of demand for testing and intensive care units (ICU), some countries may again experience fluctuating behaviors or the return of viral pandemics. Various reasons are resulting in this emerging virus in the world. Apart from the tendency to cause severe disease with a higher death rate than previous coronavirus diseases, it can spread so quickly. This study aimed to reach an optimal capacity allocation in the health care centers by intervening in government decisions and public holidays in Iran on disease control. This research is the first to analyze and develop a healthcare capacity allocation strategy by considering the mutual effects of disease outbreaks and government actions as decision aiding tools via a hybrid simulation–optimization framework. Also, we calibrate the developed hybrid simulation–optimization model for Iran on the improved SEIR framework to generate reliable outputs. The simulation results show that it is necessary to allocate some part of the health capacity to the mild symptomatic patients.

Keywords Simulation optimization · System dynamics · COVID-19 · Improved SEIR · Healthcare system · Mitigation strategy

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1 Introduction

The prevalence of epidemics in countries worldwide is inherently different in a temporal and spatial process [29]. Modeling the effects of the spread and consequences of the rapid transmission of these diseases requires a better understanding of their dynamic behaviors and how human societies deal with this phenomenon [15]. Identifying crucial cause-and-effect feedback loops makes it possible to implement control policies [21]. Because of the swift spread of the COVID-19 disease, information and components related to this disease have been used to simulate different control scenarios related to the situation in Iran.

In this study, several scenarios are simulated to investigate the effect of spatial units and factors affecting the prevalence of the COVID-19 and then compared with the historical data [10]. These scenarios are developed based on the dynamic behaviors of people in the community, the impact of hospital resource capacity, population size, disease incidence period, disease period, and disease detection power rate on the spread of the disease [3].

System Dynamics (SD) is used as the simulation methodology in this study. The SD approach refers to practical tools that help us understand and analyze complex dynamic systems [11]. This modeling method is often used for an extensive and long-term complex problems. This type brings about the details of the constituent components ignored and only analyzed at the aggregate level [24]. A Systematic review of SD by Darabi and Hosseinichimeh [9] identifies an increasing trend of its applications in health areas over the past four decades. Most studies are on regional health modeling (38%) and disease-related modeling (35%), rather than fewer of those on organizational modeling (27%).

Therefore, in the infectious disease-related modeling of SD, using the comprehensive and improved SEIR model makes it possible to provide the necessary details to model not only the impact of an agent's decisions, such as confinements or curfews protocol ruled by government, on outbreaks, epidemics, and pandemics but also that of the public holidays.

Once a system is mathematically modeled, computer-based simulations give information about its behavior. However, because of the complexity of this simulation approaches like SD, it can be difficult and costly to evaluate the objective function. The input of each variable is varied with other remaining parameters in parametric simulation techniques, and the influence on the design objective is seen, which is time-consuming and less efficient. The problem is iteratively solved using the methods known as "numerical optimization" or "simulation-based optimization". In each iteration, the solution advances closer and comes up with the optimal solution with minimal computation and time.

According to previous studies, the combination of SD and optimization models to examine the components affecting the appropriate capacity assignment in the healthcare centers has not been comprehensively studied. Combining SD simulation and static optimization approach in this work paves the way for this matter. The SD model of this proposed model is built on the improved SEIR framework by considering the influence of government as a decision-maker agent and public holidays in Iran, resulting in developing the more compatible SD model with the actual disease spread.

We expect that the results of the proposed model in this study can find the appropriate solutions for capacity allocation in the healthcare system. Using the proposed hybrid simulation model also allows epidemiologists to assess the dynamic effects and behavior of the system under different conditions in the improved SEIR framework with more reliable estimates.

The rest of the article is structured as follows. Section 2 provides a review of the literature on the research topic. In Sect. 3, the simulation modeling framework is presented. The experimental design, simulation, and simulation–optimization results are discussed in Sect. 4. Finally, the concluding remarks and future research directions are provided in Sect. 5.

2 Literature Review

Wang and Ruan [31] developed a mathematical framework to simulate the probabilistic scenarios of the SARS outbreak based on limited input data. They considered several types of entities, including susceptible, suspect, unprotected, isolated, probable, and removed. Pruyt and Hamarat [20] developed the possible dynamics of the influenza A (H1N1) pandemic variant. The model was used to illustrate Exploratory System Dynamics models as scenario generators for exploratory modeling and analysis. Viana and Brailsford [30] proposed an integrated framework of system dynamics and discrete-event simulation to model and analyze Chlamydia infection in the healthcare sector. The simulation result provided valuable insights for better management of the hospital outpatient system.

Dadlani and Kumar [8] studied the dynamics of infectious diseases based on an extended version of the susceptible-infected-susceptible (SIS) model. The random nature of the disease outbreak was modeled by a complex network method. Li and Mohebbi [16] developed an agent-based simulation model for analyzing dangerous disease outbreaks using geographic information systems (GIS) data. Sharareh et al. [26] developed alternative simulation models to predict the mortality trend and to report the statistics of the World Health Organization for the prevalence of Ebola. Shin et al. [27] developed a macro-level health system dynamics model that establishes experimental knowledge to test the case from operational and financial perspectives. Chang et al. [7] developed an agent-based model for a fine-grained computational simulation of COVID-19 epidemics in Australia. This model was calibrated to reproduce several COVID-19 transfer characteristics, including the number of reproductions, the length of the incubation and generation periods, the age-related attack rate, and the growth rate of cumulative prevalence during a sustained and relentless local transmission. Ivanov [15] developed the specific features that cause the spread of epidemic diseases as a unique type of supply chain disruption risk. Gorji et al. [13] used a simple model that includes a set of simple differential equations concerning population size, reported and unreported infections, reported and unreported improvements, and the number of deaths in Covid-19. They concluded that mass testing is more effective than social distancing in reducing the prevalence of Covid-19.

Bouchnita and Jebrane [4] addressed diffusion dynamics for COVID-19 using a multi-stage numerical simulation method. The aim was to model virus transmission via a discrete–continuous framework and compare some interventions' performance, i.e., quarantine. Zia [33] studied the simulation analysis of outbreak COVID-19 in Oman using mobility and travel patterns. They used the Global Epidemic and Mobility model, namely GLEAMviz [5], a flexible stochastic simulation model of epidemic modeling analysis. Liu et al. [17] proposed a machine learning approach to the short-term prediction of COVID-19 transmission based on multi-sources data, i.e., search engines, social media on the web, healthcare reports, news alerts, and simulation results generated by GLEAMviz tool.

Ghaffarzadegan and Rahmandad [12] focused on the prevalence of the COVID-19 disease in Iran based on data related to frequency and mortality. They developed a simple dynamic model of the epidemic to provide a more reliable picture of the disease based on available data. They designed a framework based on the generic SEIR (Susceptible, Exposed, Infected, and Recovered) model. Mehrotra et al. [18] studied a stochastic optimization model for dedicating and sharing medical resources to mitigate the risks of epidemic disease. Peng et al. [19] proposed a generalized SEIR model to analyze the COVID-19 epidemic. Ghaffarzadegan and Rahmandad [12] designed a simulation-based method for estimating the severity of an epidemic by combining different sources of data. Using data from various outlets, They showed that official estimates are at least an order of magnitude lower than the accurate distribution of the outbreak. Azarafza et al. [2] applied Deep Learning and LSTM neural network algorithms to predict COVID-19 spread in Iranian provinces. ArunKumar and Kalaga [1] proposed machine learning and time series methods to predict the rate of COVID-19 infections and recoveries at the global scale within two months. Struben [28] focused on the impact of specific interventions on coronavirus epidemics. A dynamic epidemic behavior model was developed for multidimensional policy analysis, including endogenous virus transmission, social contacts, case testing, and reporting. Calabrese and Demers [6] used a modified SEIR model to optimize test strategies under limited test capacity. Rahmandad et al. [23] focused on effective responses to the COVID-19 pandemic and the need to integrate behavioral factors such as reduced risk-based contact. A dynamic model was developed and estimated for countries with reliable test data.

The literature review shows that hybrid simulation modeling frameworks take advantage of different simulation paradigms, thus it creates a more reliable method for analyzing complex dynamic systems. This work proposes a hybrid SD simulation optimization model for capacity allocation of patient beds and testing for COVID-19 patients in healthcare systems. The contribution of this study is threefold:

First, we implement the SD model in the improved SEIR framework by imposing the dynamic impact of two factors, including government's decisions and public holidays, on the SD model.

Second, we integrate the SD model as input to the Unbounded Knapsack Problem (UKP) optimization problem for allocation capacity of testing and hospital beds between patients.

Third, the validity of the hybrid simulation model is tested using actual time-series datasets of Iran from February 26, 2020, to April 23, 2021.

3 Methodology

3.1 System Dynamics (SD) Model

The vast majority of the coronavirus simulators that have arisen in the past are based on what is known as the SEIR Model. However, in this study, an SD model is developed by improving the classical SEIR framework for modeling the spread of COVID-19 in Iran.

The flow diagram of the system dynamic model, including the model's primary variables in the stock-flow diagram, is shown in Fig. 1.

The SEIR framework is based on System Dynamics and comprises a series of stocks representing different populations and flows that generate the variations between them. In its classical form, the system comprises four distinct stocks, namely, **S**usceptible, **E**xposed, **I**nfected, and **R**emoved/**R**ecovered, that give a name to the model and represent its current state for any given point in time. The **S**usceptible refer to the population who can contract the disease, but the Exposed are those who

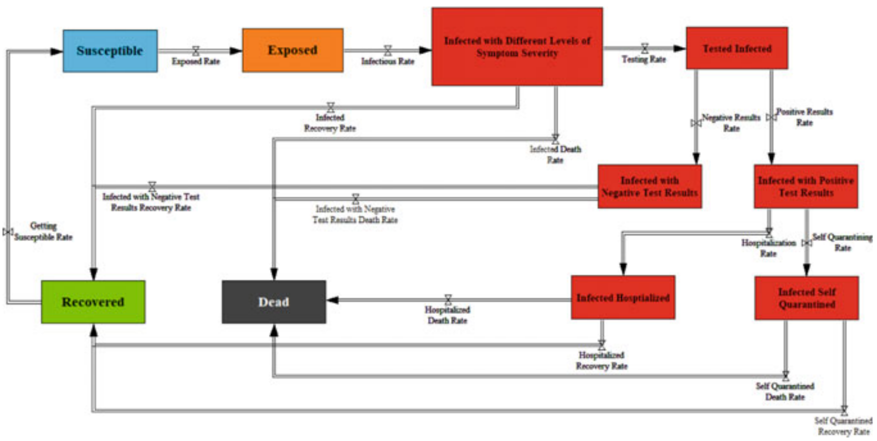

Fig. 1 A general view of the stock-flow diagram of the model

are infected but are not yet infectious. The Infected are the portion of the population that carries the disease. The Removed, also referred to as Recovered, includes the population who have become immune.

In the designed model, the same as the classic SEIR model, several susceptible will turn into exposed every day. Exposed stock shows the number of asymptomatic infected persons according to the contacts that susceptible people have with other kinds of infected people. A dynamic variable called "rate" changes a person's state from susceptible to exposed based on the number of contacts that infected people will have with the susceptible population in the SEIR model. However, in our model, we customize this rate variable, especially for Iran's case. The following equation displays the formula for the rate variable, which changes the state of susceptibility to exposure.

$$\begin{aligned} Exposed\ Rate = {} & (Total\ Exposed\ Contacts + Total\ Infected\ Contacts) \\ & * Redundancy\ Coefficient \\ & * Probability\ of\ Meeting\ a\ Susceptible \\ & * Effect\ of\ Holidays\ on\ Contact\ Rate \\ & * Effect\ of\ Government\ on\ Contact\ Rate \end{aligned} \tag{1}$$

The first two terms calculate the number of contacts leading to the infectivity by being in touch with either infected or exposed individuals. Note that in the COVID-19 case, even the exposed patients without symptoms have this ability to transmit the disease. That is why we should consider the exposed contacts besides that of the symptomatic infected.

After an incubation period, the exposed people will turn into symptomatic infected. In the classic SEIR model, there is only one infected stock; however, in the COVID-19 case, the severity of symptoms of infected persons will affect the fatality rate, recovery time, and other characteristics of the patients.

As a result, in our model, we proposed to segregate the infected stock into three other stock variables based on their disease intensity, from mild to severe. Following segregation, a particular contact rate parameter is specified for each intensity that determines the contact numbers of a person with others during a day. By doing so, the homogeneity assumption is relaxed for the infected persons.

To calculate each type of contact for each type, their special correspondence contact rate multiplies their infected stock variable. Then, we can calculate the "Total Infected Contacts" by summing these multiplications for each infected type, which determines all the contacts during a day whose one side is an infected individual.

By doing so, two issues happen: First, calculating redundant contacts, although each contact with two sides is such an unordered pair, we count them as ordered, two times, redundantly. Second, a new exposed case is generated, provided that the contacts would be between the infected and susceptible, while we count all possible contacts with the infected.

To solve the mentioned problems:

1. For the first issue, we propose using a "Redundancy Coefficient" to remove them.
2. For the second one, we multiply the previous terms by a variable called "Probability of Meeting a Susceptible," which can be determined through the following equation.

$$Probability\, of\ Meeting\ Susceptible = \frac{Susceptible}{Total\ Population} \tag{2}$$

Two factors directly affect the number of contacts in Iran's COVID case; the first is the public holidays, when people travel or gather, causing more contact. The other is COVID-19 restriction protocols acted by the government. Three different lock-down periods were scheduled and carried out in Iran between February 2020 and April 2021, bringing about fewer contacts. To consider the effect of these factors, the equation is multiplied by two functions called "Effect of Holiday on Contact Rate" and "Effect of Government on Contact Rate". During the holidays, "Effect of Holiday on Contact Rate" returns a value greater than one, otherwise equal to one. In lock-down periods, "Effect of Government on Contact Rate" returns a value between 0 and 1, otherwise equal to 1. We estimate the parameters' values of these two functions through calibration.

In the next step, after being infected, the infected patient may go to take a COVID-19 test. Taking this test depends on the availability of the testing capacity. In our model, the priority to take a test is with severe infected cases. A rate variable is assigned to each of the three infected stock variables that determine the availability of testing capacity. Due to the limited capacity for testing per day, it is impossible to fulfill all test demands. In this case, the rest patients may either die or be recovered according to correspondence death coefficient and recovery time.

After taking the test, we expect a positive result; however, because of the error probability of the test, it is likely to report wrong. Therefore, we categorized the infected patients with any intensity into two distinct groups. The first group includes the infected with a positive test result, and the other is with a negative. The latter group may either die or be recovered according to the specified recovery time and death coefficient. Nonetheless, according to the available hospital capacity, the former group will also be divided into two subgroups, including hospitalized and self-quarantined. Finally, these two subgroups may either die with a death rate defined by the death coefficient of each subgroup or be recovered regarding the recovery rate and time parameters.

According to recent research on the characteristics of the novel coronavirus, the recovered patients may be infected again after passing the immunity period. Despite the previous studies, this characteristic is involved in the model by introducing a rate variable from recovered stock variables wherein the state of the recovered patients will be changed to susceptible after the immunity period. A list of detailed descriptions of model parameters and equations is available in Appendixes 1 and 2.

3.2 Optimization Model

For this part, we use the OptQuest optimization engine of the AnyLogic software to make optimal decisions regarding testing and hospital bed capacity. To do so, these parameters for all three groups of the infected individuals are to be optimized.

Optimization in simulation exists in two major branches of operations research:

- Parametric optimization (static)—The purpose is to determine the "static" parameter values for all states. In this scenario, simulation helps when the parameters contain noise, or because of their complexity, the issue of evaluation would need excessive computer time.
- Control of Optimization (dynamic)—Optimal control is per state, and the results in each. The simulation can produce random samples and address complicated and significant issues in this scenario. Because of the complexity of our model, we intend to use static optimization:

In this approach, we import our proposed mathematical modeling in the OptQuest optimization engine in the AnyLogic to optimize the desired parameters in the SD simulation model. The proposed optimization model follows the formulation of **UKP**, which is a well-known resource allocation problem in real-world decision-making processes.

UKP can be formulated as it restricts the number of copies of each item to a non-negative integer. Given a set of n items numbered from 1 up to n, each with a weight and a value, along with a maximum weight capacity W.

$$Maximize \sum_{i=1}^{n} v_i x_i \tag{3}$$

Subject to

$$\sum_{i=1}^{n} w_i x_i \leq W \tag{4}$$

$$x_i \geq 0, x_i \subset Z \tag{5}$$

Solving this problem for both testing and hospital bed capacity let us get the optimal allocation strategy for healthcare system resources between three different groups of the infected. We call this static approach optimization because a constant value will be assigned to the parameters after conducting the simulation–optimization experiment. The parameters will not vary during the simulation course.

4 Experimental Validation

4.1 The Experimental Protocol

The SD model is simulated under three different scenarios. Table 1 provides a summary of these scenarios. At first, the SD model is simulated, and the results are used to validate the SD model. In the following scenarios, the SD model is simulated, considering the optimal values for the health capacity parameters in the model. These optimal values are obtained by the simulation–optimization experiment conducted in AnyLogic.

First scenario: The simple SD model

We simulated the SD model with the original parameter values in the first scenario to prepare a valid simulation model for simulation–optimization experiments. There are a lot of parameters in our SD models that should be determined. Some of them are determined through calibration, e.g., "Redundancy Coefficient" and "Normal Contact Rate". Some of the parameter values are estimated, and the other ones are determined from the literature.

Second scenario: SD model with optimal health capacities using optimization model 1

In this scenario, the SD model is simulated by the optimal health capacity parameters obtained by the simulation optimization. The optimization model is trying to maximize the utilization of healthcare capacity. By healthcare capacity, we mean the number of hospital beds assigned for COVID cases. The following optimization model is used for this scenario, and Table 2 describes the variables used in this model.

$$Max \;\; 0.8x_1 + 0.15x_2 + 0.05x_3 \tag{6}$$

$$s.t. \;\; x_1 + x_2 + x_3 \leq 30000 \tag{7}$$

Table 1 Three scenarios of simulation

Scenarios	Model	Details
First scenario	The simple SD model	The results of this simulation are used for validation
Second scenario	The simulation–optimization model	A constraint adds the optimization model on the capacity of severe
Third scenario	The simulation–optimization model	A constraint adds the optimization model on the capacity of mild

Table 2 Mapping between variables' full name and their short form in the optimization model

Variable full name	Short form in the optimization model
Mild health capacity*	x_1
Moderate health capacity	x_2
Severe health capacity	x_3

*Health capacity means the number of beds devoted to the infected patients with different levels of symptom severity

$$x_3 \geq 2025 \tag{8}$$

$$x_i \geq 0, x_i \subset z \tag{9}$$

The first constraint is to guarantee that the total number of assigned beds will not exceed the total available capacity. The second constraint is considered to make sure that we will, at least, have 2025 beds for severe patients. 2025 is the average number of beds that the SD model considered for severe patients.

Third scenario: SD model with optimal health capacities using optimization model 2

In this scenario, we used a different optimization model to examine a different allocation strategy on the results. In this strategy, the focus will be on the mild symptomatic patients, and the optimization model will assign at least half of the capacity to the mild symptomatic patients. The decision variables and the objective function are as same as in the previous model. There is just one change in the second constraint. In this model, we considered a low bound for the mild health capacity instead of the severe patients, and the value of the low bound is considered 15,000.

4.1.1 Implementation

Vensim and AnyLogic software are used for implementing the proposed model. The SD model is simulated with Vensim, and the simulation–optimization part is implemented in AnyLogic using OptQuest Optimization Engine. The results are obtained by using an Acer Aspire PC with a processor speed of 1.6 GHz.

4.2 *Results*

4.2.1 Validation and Verification of SD Model

One of the main methods of validation of the SD model is a comparison with the historical data. There are three primary variables that we have their data to be used for the validation, including infected cases, dead, and recovered patients. Figures 2, 3, and 4 show the historical data, and the simulated results for the three mentioned variables.

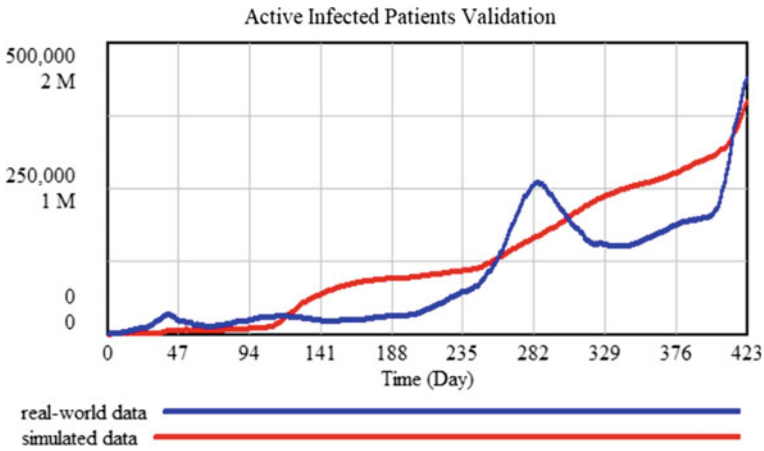

Fig. 2 Comparison of the real-world data and the simulated data for the infected patients

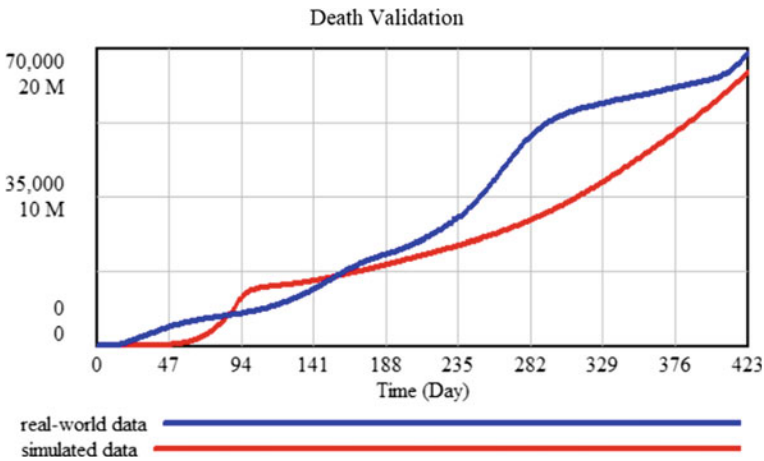

Fig. 3 Comparison of the real-world data and the simulated data for the dead variable

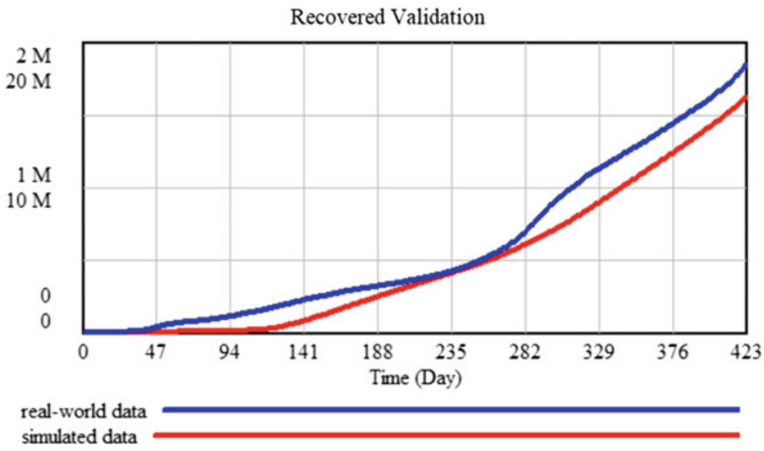

Fig. 4 Comparison of the real-world data and the simulated data for the recovered variable

As the figures show, the simulated data displays the same trend as the real-world data.

The sensitivity test is another validation method. The model's behavior will be examined in this method when some parameters are set to their critical values. To check the validity of the model with this method, all the death coefficient parameters were set to 0. This means that there should not be any dead cases in the model. Figure 5 shows the dead graph when the model is simulated, considering 0 as the value of the death coefficients.

As Fig. 5 shows, the dead variable does not change through the simulation course, and it remains 19 during the simulation that is its initial value.

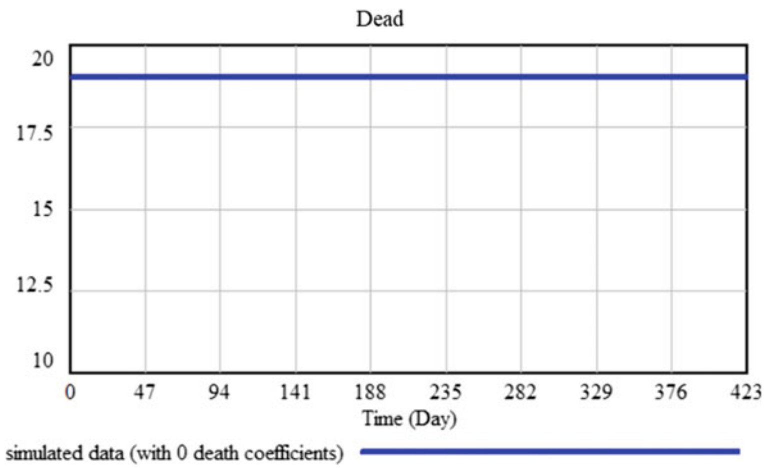

Fig. 5 Dead graph while considering 0 as the value of the death coefficients

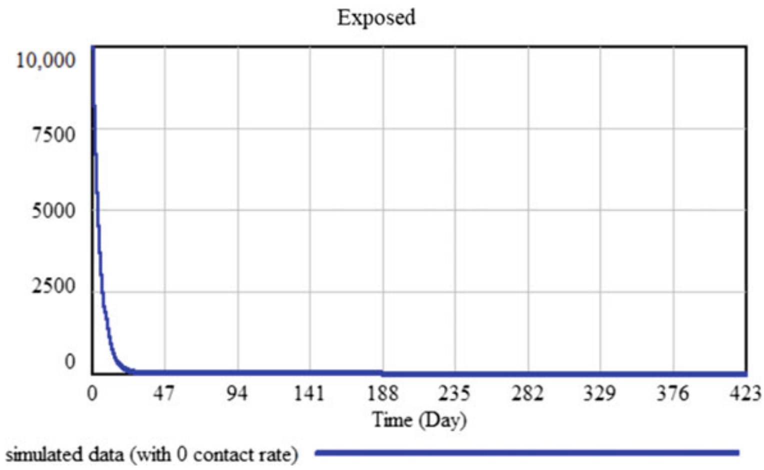

Fig. 6 Exposed graph while considering 0 as the value of "normal contact rate" parameter

In addition to setting the death coefficient to 0, another parameter is also considered 0 to examine the model's validity. This time the "Normal Contact Rate" is set 0. The simulation result indicates that there are no contacts between the population, so there should not be newly exposed cases in the model. Figure 6 shows the exposed graph when the model is simulated, considering 0 as the "Normal Contact Rate" value.

As Fig. 6 shows, the exposed variable does not increase through the simulation course, and it decreases from its initial value to 0 and remains 0 until the end of the simulation.

4.2.2 Simulation–Optimization Results

As mentioned before, we use the validated SD model to conduct a simulation–optimization experiment for finding the optimal values of the health capacity parameters. We used two different experiments, and the results are provided in the following paragraphs.

First experiment: SD model with optimal health capacities using optimization model 1

The simulation–optimization experiment is run in AnyLogic using the first optimization model. Figure 7 displays a view of the experiment when it is completed. The simulation–optimization method converges after 238 iterations.

Table 3 provides the optimal values for the health capacities considering two different optimization models.

The results of this experiment seem to be like the original SD simulation and the real world because the priority is with the patients with severe and moderate

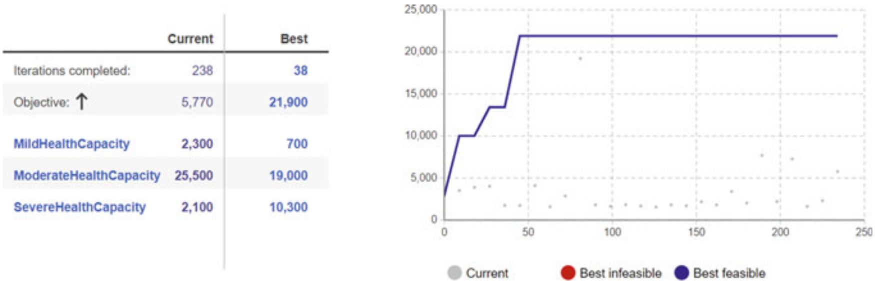

Fig. 7 A completed simulation–optimization experiment in AnyLogic for the first optimization model

Table 3 The simulation–optimization results of the optimization models

Parameter name	Model 1 results	Model 2 results
Mild health capacity	700	15,200
Moderate health capacity	19,000	300
Severe health capacity	10,300	10,500

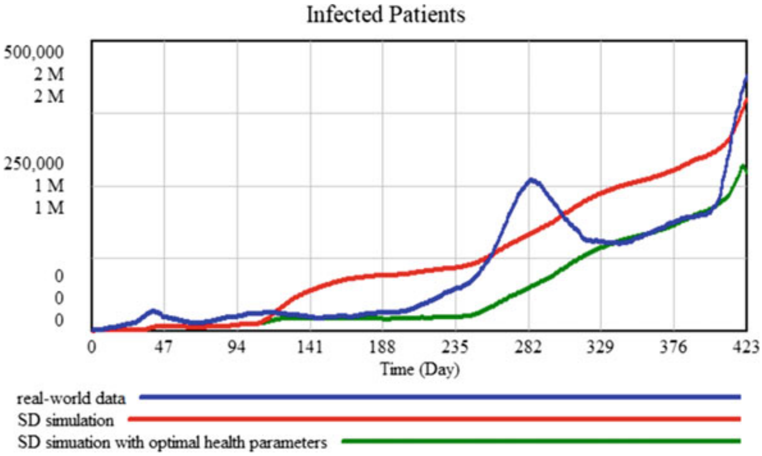

Fig. 8 Comparing optimal resource allocations with model 1 with the original model and actual data for the infected patients' variable

symptoms. However, in the SD model, the capacity for the mild patients is 0 and in this experiment is 700.

To understand the effect of optimal resource allocation on the model outputs, the SD model is simulated using the optimal parameter values obtained by the first experiment.

Figures 8, 9, and 10 compare the simulation results by the optimal parameters with the baseline SD simulation results and the real-world data for the three primary variables of the model i.e., infected patients, dead, and recovered cases.

As the figure shows, the simulation with optimal allocation improves the system's behavior in all three graphs. The number of infected and dead patients will be lower than the original model. The simulation result implies that it is better to consider a capacity for the patients with mild symptoms, and it is not optimal not to hospitalize all the patients with mild symptoms.

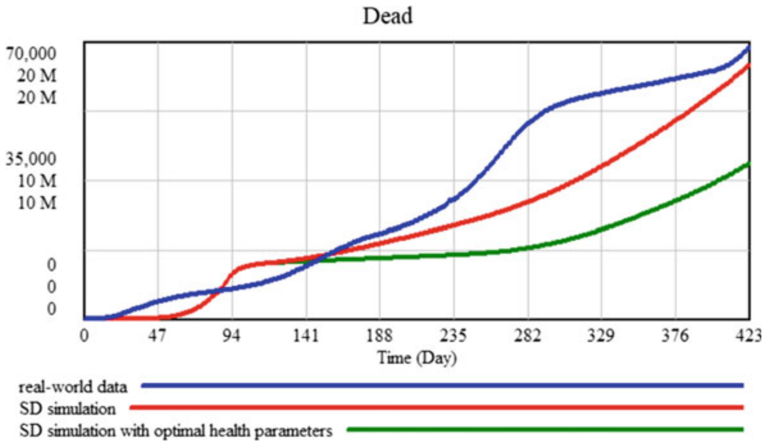

Fig. 9 Comparing optimal resource allocations with model 1 with the original model and actual data for the dead variable

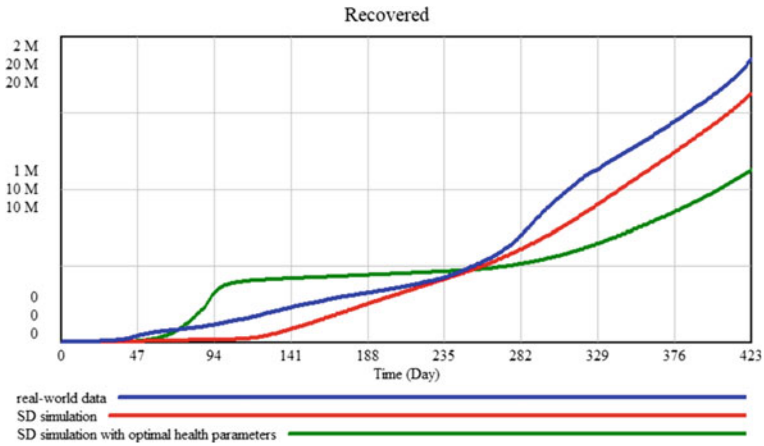

Fig. 10 Comparing optimal resource allocations with model 1 with the original model and actual data for the recovered variable

Second experiment: SD model with optimal health capacities using optimization model 2

The simulation–optimization experiment is run in AnyLogic using the second optimization model. Figure 11 displays a view of the experiment when it is completed. The simulation–optimization converges after 252 iterations.

Table 3 provides the optimal values for the health capacities using the simulation–optimization method considering the second optimization model.

The results of this allocation are entirely different. In this model, most of the capacities are assigned to the patients with mild symptoms. When we run the SD model with these parameters, the results will be like the graphs shown in Figs. 12, 13, and 14.

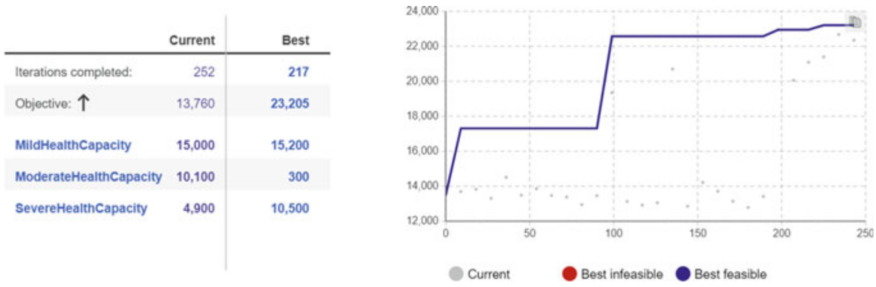

Fig. 11 The completed simulation–optimization experiment in AnyLogic for the first optimization model

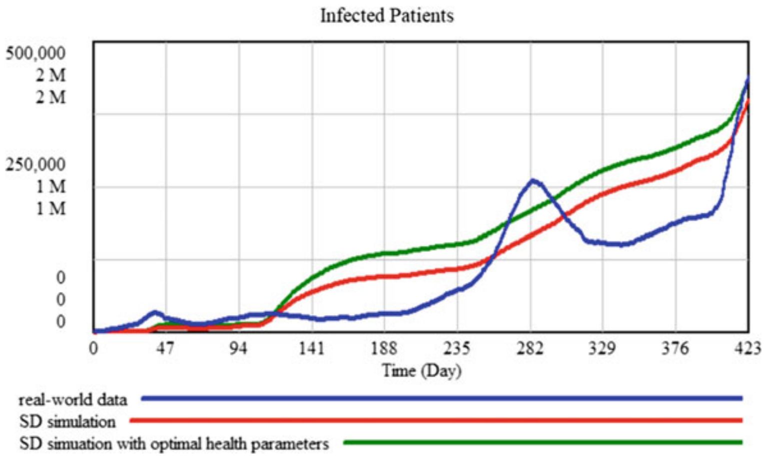

Fig. 12 Comparing optimal resource allocations with model 2 with the original model and actual data for the infected patients' variable

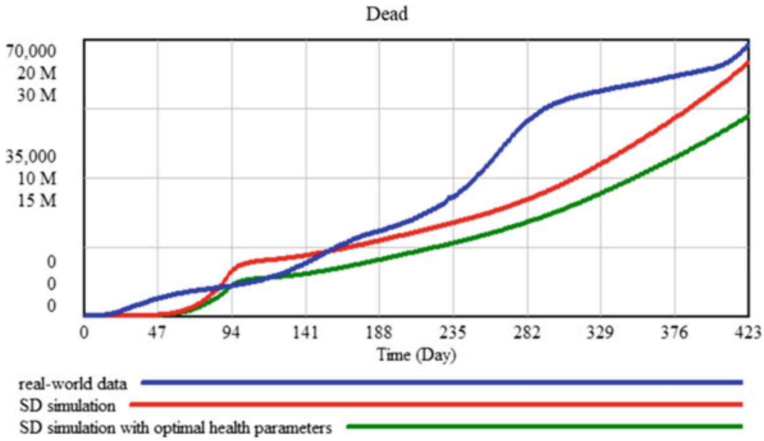

Fig. 13 Comparing optimal resource allocations with model 2 with the original model and actual data for the dead variable

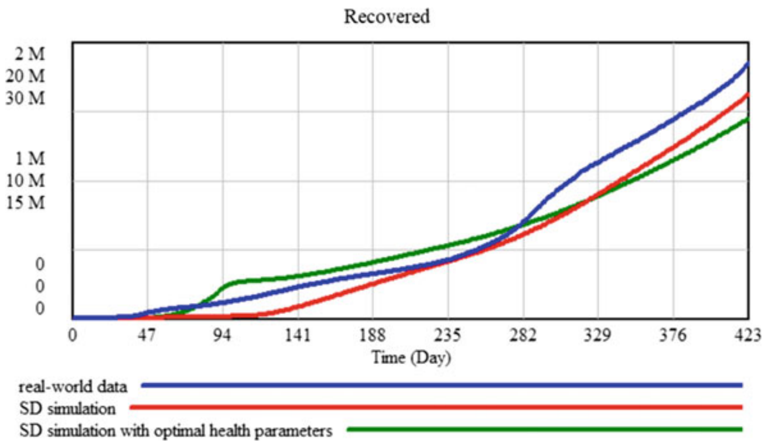

Fig. 14 Comparing optimal resource with model 2 with the original model and actual data for the recovered variable

As a result of implementing this scenario, the number of infected patients will be higher; however, the number of dead patients will be lower. The recovered do not change much.

Analyzing the results of the two mentioned scenarios leads us to conclude that it is necessary to allocate some part of the health capacity to the mild symptomatic patients. If we allocate a large portion of the health capacity to the mild symptomatic patients, only the number of dead cases will be lower than the original SD model. Still, suppose we assign most of the health capacity to the severe and moderate symptomatic patients and assign a small amount to the mild symptomatic patients.

In that case, the behavior of all three primary variables will be better than the original SD model.

5 Conclusion

Today, all countries worldwide, including Iran, are still facing the threat of the COVID-19 illness spreading. Some nations may see changing behaviors or the reappearance of viral pandemics due to the healthcare system's limited capacity and the danger of a repeat of demand for testing and intensive care units.

Numerous factors have contributed to the spread of this new virus across the world. Except for its propensity for causing serious conditions with a greater mortality rate than earlier coronavirus infections, it spreads extremely fast. By interfering in governmental policies and public holidays in Iran on illness management, this study attempted to achieve optimal capacity allocation in medical centers.

This is the first study to examine and create a healthcare capacity allocation plan using a hybrid simulation–optimization approach to incorporate the mutual impacts of disease outbreaks and government actions. Using the developed simulation model, public health experts may analyze the system's dynamic impacts and behavior under various situations in the enhanced SEIR framework, resulting in more reliable estimations.

Among the perspectives of this work, the next challenge is to integrate the proposed simulation–optimization approach with a dynamic optimization model for testing capacity allocation. To be more compatible with reality, another extension of this work would concern the multiple agents simultaneously. For better interactions between these agents, we plan on proposing more comprehensive agent-based modeling to reach compromise results close to the real-world data.

Appendix 1

Name	Explanation	Quantity	Unit	Source
Susceptible	Stock's initial value	83,000,000	Person	Determined
Exposed	Stock's initial value	10,000	Person	Estimated
Mild infected	Stock's initial value	5300	Person	Estimated
Moderate infected	Stock's initial value	1000	Person	Estimated
Severe infected	Stock's initial value	300	Person	Estimated
Mild infected tested	Stock's initial value	0	Person	Given data

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Name	Explanation	Quantity	Unit	Source
Moderate infected tested	Stock's initial value	0	Person	Given data
Severe infected tested	Stock's initial value	0	Person	Given data
MIT covid+	Stock's initial value	0	Person	Given data
MIT covid+	Stock's initial value	0	Person	Given data
MMIT covid+	Stock's initial value	0	Person	Given data
MMIT covid+	Stock's initial value	0	Person	Given data
SIT covid+	Stock's initial value	0	Person	Given data
SIT covid+	Stock's initial value	0	Person	Given data
MIT covid−	Stock's initial value	0	Person	Given data
MIT covid−	Stock's initial value	0	Person	Given data
MMIT covid−	Stock's initial value	0	Person	Given data
MMIT covid−	Stock's initial value	0	Person	Given data
SIT covid−	Stock's initial value	0	Person	Given data
SIT covid−	Stock's initial value	0	Person	Given data
Documented recovered	Stock's initial value	54	Person	Given data
Documented death	Stock's initial value	19	Person	Given data
Mild self-quarantined	Stock's initial value	0	Person	Assumed
Moderate self-quarantined	Stock's initial value	0	Person	Assumed
Severe self-quarantined	Stock's initial value	0	Person	Assumed
Mild hospitalized	Stock's initial value	0	Person	Assumed
Moderate hospitalized	Stock's initial value	0	Person	Assumed
Severe hospitalized	Stock's initial value	0	Person	Assumed
Holiday contact increase coefficient	How many times contact rates, in holidays, are greater than normal situations	3.2	DNL	Calibrated
Lock-down decrease coefficient	How many times contact rates, in lock-down, are less than normal situations	0.55	DNL	Calibrated

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Name	Explanation	Quantity	Unit	Source
Exposed contact rate	Number of contacts that each exposed person has during one day	Normal contact rate	Contact	Same as normal contact rate, because the person has not been detected yet
Mild SQ	Number of contacts that each mild self quarantined person has during one day	0	Contact	It is assumed that people in quarantine, will not contact the other ones
Mild H	Number of contacts that each mild hospitalized person has during one day	0	Contact	It is assumed that people in quarantine, will not contact the other ones
Moderate SQ	Number of contacts that each moderate self quarantined person has during one day	0	Contact	It is assumed that people in quarantine, will not contact the other ones
Moderate H	Number of contacts that each moderate hospitalized person has during one day	0	Contact	It is assumed that people in quarantine, will not contact the other ones
Severe SQ	Number of contacts that each severe self quarantined person has during one day	0	Contact	It is assumed that people in quarantine, will not contact the other ones
Severe H	Number of contacts that each severe hospitalized person has during one day	0	Contact	It is assumed that people in quarantine, will not contact the other ones
Severe infected contact rate	Number of contacts that each severe infected person has during one day	Normal contact rate	Contact	Same as normal contact rate, because the person has not been detected yet
Moderate infected contact rate	Number of contacts that each moderate infected person has during one day	Normal contact rate	Contact	Same as normal contact rate, because the person has not been detected yet
Mild infected contact rate	Number of contacts that each mild infected person has during one day	Normal contact rate	Contact	Same as normal contact rate, because the person has not been detected yet
Severe infected tested contact rate	Number of contacts that each severe infected tested person has during one day	0.5* normal contact rate	Contact	Assumed*

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Name	Explanation	Quantity	Unit	Source
Moderate infected tested contact rate	Number of contacts that each moderate infected tested person has during one day	0.5* normal contact rate	Contact	Assumed*
Mild infected tested contact rate	Number of contacts that each mild infected tested person has during one day	0.5* normal contact rate	Contact	Assumed*
SIT covid+ contact rate	Number of contacts that each SIT covid+ person has during one day	0	Contact	It is assumed that after having a positive test people will go to quarantine and do not contact the other ones
MIT covid+ contact rate	Number of contacts that each MIT covid+ person has during one day	0	Contact	It is assumed that after having a positive test people will go to quarantine and do not contact the other ones
MMIT covid+ contact rate	Number of contacts that each MMIT covid+ person has during one day	0	Contact	It is assumed that after having a positive test people will go to quarantine and do not contact the other ones
SIT covid− contact rate	Number of contacts that each SIT covid− person has during one day	Normal contact rate	Contact	Same as normal contact rate, because the test is negative
MIT covid− contact rate	Number of contacts that each MIT covid− person has during one day	Normal contact rate	Contact	Same as normal contact rate, because the test is negative
MMIT covid− contact rate	Number of contacts that each MMIT covid− person has during one day	Normal contact rate	Contact	Same as normal contact rate, because the test is negative
Testing data	Number of tests that can be taken in each day	Look-up	Number	We have the data
Infectivity	Probability of transmitting disease in a contact	0.09		

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Name	Explanation	Quantity	Unit	Source
Total health capacity	Number of available beds for covid cases	30,000		
Immunity period	The number of days that a recovered person won't be infected	8 moths (240 days)	Day	Reference (https://www.healthline.com/health-news/how-long-does-immunity-last-after-covid-19-what-we-know)
Moderate coefficient	The percentage of the infected cases that have moderate symptoms	0.15	DNL	WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19)
Mild coefficient	The percentage of the infected cases that have mild symptoms	0.8	DNL	WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19)
Severe coefficient	The percentage of the infected cases that have severe symptoms	0.05	DNL	WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19)
Incubation period	The number of days that an infected person has no symptoms	5	Days	[13] WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19)
MMI death coefficient	The percentage of mild infected people which die through covid	0	DNL	In most of the papers that studied a number of covid cases, all the patients with mild symptoms recovered form covid

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Name	Explanation	Quantity	Unit	Source
MI death coefficient	The percentage of moderate infected people which die through covid	0	DNL	In most of the papers that studied a number of covid cases, all the patients with moderate symptoms recovered form covid
SI death coefficient	The percentage of severe infected people which die through covid	0.49	DNL	[30]
MMI recovery time	The number of days that it takes for an infected person with mild symptoms to recover	5	Days	WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19)
MI recovery time	The number of days that it takes for an infected person with moderate symptoms to recover	10	Days	WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19)
SI recovery time	The number of days that it takes for an infected person with severe symptoms to recover	14	Days	WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19)
Mild self-quarantined recovery time	The number of days that it takes for an infected person with mild symptoms, who is staying at home, to recover	5	Days	Same as the MMI recovery time
Moderate self-quarantined recovery time	The number of days that it takes for an infected person with moderate symptoms, who is staying at home, to recover	10	Days	Same as the MI recovery time

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Name	Explanation	Quantity	Unit	Source
Severe self-quarantined recovery time	The number of days that it takes for an infected person with severe symptoms, who is staying at home, to recover	14	Days	Same as the SI recovery time
Mild hospitalized recovery time	The number of days that it takes for an infected person with mild symptoms, who is staying at hospital, to recover	3	Days	[23]
Moderate hospitalized recovery time	The number of days that it takes for an infected person with moderate symptoms, who is staying at hospital, to recover	5	Days	[23]
Severe hospitalized recovery time	The number of days that it takes for an infected person with severe symptoms, who is staying at hospital, to recover	9	Days	[23]
Normal contact rate	The average number of contacts for a person in Iran in normal condition	2	Contact	Calibrated
Testing error	The percentage of tests that have wrong results	0.3	DNL	[20]

*It is assumed that the contact rate of the persons who are waiting to know their test results are less than normal contact. We assumed that their contact rate is half of the "Normal Contact Rate". This assumption is because of the uncertainty about the test result. In this case, the patients are not sure whether they are infected or not. Although they will not be in quarantine, they are more careful than the normal situation regarding their contacts with other people and will avoid unnecessary contacts. As a result, their contact rate parameter will be lower than the normal situation

Appendix 2: Differential Equations

In this section, the differential equations which builds the proposed model are provided.

$$E_r = GS_r - \frac{dS}{dt}$$
$$I_{1r} = E_r - I_{2r} - I_{3r} - \frac{dE}{dt}$$
$$I_{2r} = E_r - I_{1r} - I_{3r} - \frac{dE}{dt}$$
$$I_{3r} = E_r - I_{1r} - I_{2r} - \frac{dE}{dt}$$

$$D_r I_1 = I_{1r} - I_{1Tr} - \frac{dI_1}{dt}$$
$$D_r I_2 = I_{2r} - I_{2Tr} - \frac{dI_2}{dt}$$
$$D_r I_3 = I_{3r} - I_{3Tr} - \frac{dI_3}{dt}$$

$$I_{1Tr} = I_{1TNr} + I_{1TPr} + \frac{dI_{1T}}{dt}$$
$$I_{2Tr} = I_{2TNr} + I_{2TPr} + \frac{dI_{2T}}{dt}$$
$$I_{3Tr} = I_{3TNr} + I_{3TPr} + \frac{dI_{3T}}{dt}$$

$$I_{1TPr} = SQ_{1r} + H_{1r} + \frac{dI_{1TP}}{dt}$$
$$I_{2TPr} = SQ_{2r} + H_{2r} + \frac{dI_{2TP}}{dt}$$
$$I_{3TPr} = SQ_{3r} + H_{3r} + \frac{dI_{3TP}}{dt}$$

$$I_{1TNr} = R_r I_{1TN} + D_r I_{1TN} + \frac{dI_{1TN}}{dt}$$
$$I_{2TNr} = R_r I_{2TN} + D_r I_{2TN} + \frac{dI_{2TN}}{dt}$$
$$I_{3TNr} = R_r I_{3TN} + D_r I_{3TN} + \frac{dI_{3TN}}{dt}$$

$$SQ_{1r} = R_r SQ_1 + D_r SQ_1 + \frac{dSQ_1}{dt}$$
$$SQ_{2r} = R_r SQ_2 + D_r SQ_2 + \frac{dSQ_2}{dt}$$
$$SQ_{3r} = R_r SQ_3 + D_r SQ_3 + \frac{dSQ_3}{dt}$$

$$H_{1r} = R_r H_1 + D_r H_1 + \frac{dH_1}{dt}$$
$$H_{2r} = R_r H_2 + D_r H_2 + \frac{dH_2}{dt}$$
$$H_{3r} = R_r H_3 + D_r H_3 + \frac{dH_3}{dt}$$

$$\frac{dR}{dt} = R_r SQ_1 + R_r SQ_2 + R_r SQ_3 + R_r H_1 + R_r H_2 + R_r H_3 - GS_r$$

$$\frac{dD}{dt} = D_r SQ_1 + D_r SQ_2 + D_r SQ_3 + D_r H_1 + D_r H_2 + D_r H_3 + D_r I_1 + D_r I_2 + D_r I_3 + D_r I_{1TN} + D_r I_{2TN} + D_r I_{3TN}$$

Full variable name	Type (stock/flow)	Short form
Susceptible	Stock	S
Exposed	Stock	E
Mild infected	Stock	I_1
Moderate infected	Stock	I_2
Severe infected	Stock	I_3
Mild infected tested	Stock	I_{1T}
Moderate infected tested	Stock	I_{2T}
Severe infected tested	Stock	I_{3T}
Mild infected tested with negative results	Stock	I_{1TN}
Mild infected tested with positive results	Stock	I_{1TP}
Moderate infected tested with negative results	Stock	I_{2TN}
Moderate infected tested with positive results	Stock	I_{2TP}
Severe infected tested with negative results	Stock	I_{3TN}
Severe infected tested with positive results	Stock	I_{3TP}
Mild self quarantined	Stock	SQ_1
Mild hospitalized	Stock	H_1
Moderate self quarantined	Stock	SQ_2
Moderate hospitalized	Stock	H_2
Severe self quarantined	Stock	SQ_3
Severe hospitalized	Stock	H_3
Dead	Stock	D
Recovered	Stock	R
Exposure rate	Flow	E_r
Mild infectious rate	Flow	I_{1r}
Moderate infectious rate	Flow	I_{2r}

(continued)

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Full variable name	Type (stock/flow)	Short form
Severe infectious rate	Flow	I_{3r}
Mild infected death rate	Flow	D_rI_1
Moderate infected death rate	Flow	D_rI_2
Severe infected death rate	Flow	D_rI_3
Mild cases testing rate	Flow	I_{1Tr}
Moderate cases testing rate	Flow	I_{2Tr}
Severe cases testing rate	Flow	I_{3Tr}
Mild cases negative test result	Flow	I_{1TNr}
Mild cases positive test result	Flow	I_{1TPr}
Moderate cases negative test result	Flow	I_{2TNr}
Moderate cases positive test result	Flow	I_{2TPr}
Severe cases negative test result	Flow	I_{3TNr}
Severe cases positive test result	Flow	I_{3TPr}
Mild infected tested with negative results recovery	Flow	R_rI_{1TN}
Mild infected tested with negative results death	Flow	D_rI_{1TN}
Moderate infected tested with negative results recovery	Flow	R_rI_{2TN}
Moderate infected tested with negative results death	Flow	D_rI_{2TN}
Severe infected tested with negative results recovery	Flow	R_rI_{3TN}
Severe infected tested with negative results death	Flow	D_rI_{3TN}
Mild infected tested with positive results self quarantining	Flow	SQ_{1r}
Mild infected tested with positive results hospitalization	Flow	H_{1r}
Moderate infected tested with positive results self quarantining	Flow	SQ_{2r}
Moderate infected tested with positive results hospitalization	Flow	H_{2r}
Severe infected tested with positive results self quarantining	Flow	SQ_{3r}
Severe infected tested with positive results hospitalization	Flow	H_{3r}
Mild self quarantined recovery	Flow	R_rSQ_1
Mild self quarantined death	Flow	D_rSQ_1
Moderate self quarantined recovery	Flow	R_rSQ_2
Moderate self quarantined death	Flow	D_rSQ_2
Severe self quarantined recovery	Flow	R_rSQ_3
Severe self quarantined death	Flow	D_rSQ_3
Mild hospitalized recovery	Flow	R_rH_1
Mild hospitalized death	Flow	DrH1
Moderate hospitalized recovery	Flow	R_rH_2
Moderate hospitalized death	Flow	D_rH_2
Severe self quarantined recovery	Flow	R_rH_3
Severe self quarantined death	Flow	D_rH_3

(continued)

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Full variable name	Type (stock/flow)	Short form
Getting susceptible	Flow	GS_r

References

1. ArunKumar, K.E., Kalaga, D.V.: Forecasting the dynamics of cumulative COVID-19 cases (confirmed, recovered and deaths) for top-16 countries using statistical machine learning models: auto-regressive integrated moving average (ARIMA) and seasonal auto-regressive integrated moving average. Appl. Soft Comput. **103**, 107161 (2021)
2. Azarafza, M., Azarafza, M., Tanha, J.: COVID-19 infection forecasting based on deep learning in Iran. MedRxiv (2020). https://doi.org/10.1101/2020.05.16.20104182
3. Biswas, K., Khaleque, A., Sen, P.: Covid-19 spread: reproduction of data and prediction using a SIR model on Euclidean network (2020). arXiv preprint arXiv:2003.07063
4. Bouchnita, A., Jebrane, A.: A hybrid multi-scale model of COVID-19 transmission dynamics to assess the potential of non-pharmaceutical interventions. Chaos **138**, 109941 (2020)
5. Broeck, W.V.D., Gioannini, C., Gonçalves, B., Quaggiotto, M., Colizza, V., Vespignani, A.: The GLEaMviz computational tool, a publicly available software to explore realistic epidemic spreading scenarios at the global scale. BMC Infect. Dis. **11**, 37 (2011). https://doi.org/10.1186/1471-2334-11-37
6. Calabrese, J.M., Demers, J.: How optimal allocation of limited testing capacity changes epidemic dynamics. Medrxiv.Org (2020). https://doi.org/10.1101/2020.12.21.20248431
7. Chang, S.L., Harding, N., Zachreson, C., Cliff, O.M., Prokopenko, M.: Modelling transmission and control of the COVID-19 pandemic in Australia. Nat. Commun. **11**(1), 1–13 (2020)
8. Dadlani, A., Kumar, M.S.: System dynamics of a refined epidemic model for infection propagation over complex networks. IEEE Syst. J. **10**(4), 1316–1325 (2014)
9. Darabi, N., Hosseinichimeh, N.: System dynamics modeling in health and medicine: a systematic literature review. Syst. Dyn. Rev. **36**(1), 29–73 (2020). https://doi.org/10.1002/sdr.1646
10. Fanelli, D., Piazza, F.: Analysis and forecast of COVID-19 spreading in China, Italy and France. Chaos, Solitons Fractals **134**,109761 (2020)
11. Forrester, J.W.: System dynamics, systems thinking, and soft OR. Syst. Dyn. Rev. **10**(2–3), 245–256 (1994). https://doi.org/10.1002/sdr.4260100211
12. Ghaffarzadegan, N., Rahmandad, H.: Simulation-based estimation of the early spread of COVID-19 in Iran: actual versus confirmed cases. Syst. Dyn. Rev. **36**(1), 101–129 (2020). https://doi.org/10.1002/sdr.1655
13. Gorji, H., Arnoldini, M., Jenny, D.F., Hardt, W.-D., Jenny, P.: Dynamic modeling to identify mitigation strategies for Covid-19 pandemic. Medrxiv.Org. https://doi.org/10.1101/2020.03.27.20045237
14. Guan, W., et al.: Clinical characteristics of coronavirus disease 2019 in China. N. Engl. J. Med. **382**(18), 1708–1720 (2020). https://doi.org/10.1056/nejmoa2002032
15. Ivanov, D.: Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transp. Res. Part E: Logist. Transp. Rev. **136**, 101922 (2020)
16. Li, X., Mohebbi, S.: Modeling diffusion of epidemic diseases via agent-based simulation. In: Annual Conference. Proceedings. Institute of Industrial and Systems Engineers (IISE) (2015)
17. Liu, D., Clemente, L., Poirier, C., Ding, X., Chinazzi, M., Davis, J.T., Vespignani, A., Santillana, M.: A machine learning methodology for real-time forecasting of the 2019–2020 COVID-19 outbreak using internet searches, news alerts, and estimates from mechanistic models (2020). arXiv preprint arXiv:2004.04019

18. Mehrotra, S., Rahimian, H., Barah, M., Luo, F., Schantz, K.: A Model of supply-chain decisions for resource sharing with an application to ventilator allocation to combat COVID-19. Nav. Res. Logist. **67**(5), 303–320 (2020). https://doi.org/10.1002/nav.21905
19. Peng, L., Yang, W., Zhang, D., Zhuge, C., Hong, L.: Epidemic analysis of COVID-19 in China by dynamical modeling (2020). arXiv preprint arXiv:2002.06563
20. Pruyt, E., Hamarat, C.: The influenza A(H1N1)v pandemic: an exploratory system dynamics approach. In: Proceedings of the 28th International Conference of the System Dynamics Society, Seoul, Korea, 25–29 July 2010. System Dynamics Society
21. Rădulescu, A., Williams, C., Cavanagh, K.: Management strategies in a SEIR-type model of COVID 19 community spread. Sci Rep **10**(1), 1–16 (2020)
22. Rahmandad, H., Lim, T.Y., Sterman, J.: Behavioral dynamics of COVID-19: estimating under-reporting, multiple waves, and adherence fatigue across 92 nations. Syst. Dyn. Rev. **37**(1), 5–31 (2020). https://doi.org/10.1002/sdr.1673
23. Rahmandad, H., Lim, T.Y., Sterman, J.: Behavioral dynamics of COVID-19: estimating under-reporting, multiple waves, and adherence fatigue across 92 nations. Medrxiv.Org, 2020–06 (2021)
24. Randers, J.: From limits to growth to sustainable development or SD (sustainable development) in a SD (system dynamics) perspective. Syst. Dyn. Rev.: J. Syst. Dyn. Soc. **16**(3), 213–224 (2000)
25. Rees, E.M., et al.: COVID-19 length of hospital stay : a systematic review and data synthesis (2020)
26. Sharareh, N., Sabounchi, N.S., Sayama, H., MacDonald, R.: The Ebola crisis and the corresponding public behavior: a system dynamics approach. PLoS Curr. **8**, (2016)
27. Shin, N., Kwag, T., Sangwook, P., Kim, Y.H.: Effects of operational decisions on the diffusion of epidemic disease: a system dynamics modeling of the MERS-CoV outbreak in South Korea. J. Theor. Biol. **421**, 39–50 (2017)
28. Struben, J.: The coronavirus disease (COVID-19) pandemic: simulation-based assessment of outbreak responses and postpeak strategies. Wiley Online Libr. **36**(3), 247–293 (2020). https://doi.org/10.1002/sdr.1660
29. Velavan, T.P., Meyer, C.G.: The COVID-19 epidemic. Trop. Med. Int. Health **25**(3), 278 (2020)
30. Viana, J.O.E., Brailsford, S.C.: Combining discrete-event simulation and system dynamics in a healthcare setting: a composite model for Chlamydia infection. Eur. J. Oper. Res. **237**(1), 196–206 (2014)
31. Wang, W., Ruan, S.: Simulating the SARS outbreak in Beijing with limited data. J. Theor. Biol. **227**(3), 369–379 (2004)
32. Wu, Z., McGoogan, J.M.: Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China. JAMA **323**(13), 1239 (2020). https://doi.org/10.1001/jama.2020.2648
33. Zia, K.: COVID-19 outbreak in Oman: model-driven impact analysis and challenges. Medrxiv.Org (2020). https://doi.org/10.1101/2020.04.02.20050666

Ensuring a Superior Level of Prepareness and Readiness by Adopting a Knowledge-Based Network-Centric Approach Leveraging Information Systems for Emergency and Disaster Management

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Abstract In December 2019 cases of pneumonia were first detected. By April 2020 the global pandemic called COVID-19 was declared by the WHO. As of January 2021, nearly 2 million people globally had died from COVID and numbers continue to grow with many areas around the globe still in crisis mode while other parts toggle between lock down and opening up again. Since June 2021, there are still concerning out breaks of COVID with new variants such as the "Indian variant" that continue to create catastrophes in different countries even as vaccine are being rolled out. By any measure, COVD is a global emergency and disaster situation (E&DS). Such E&DS events serve to underscore the utter chaos that ensues both during and in the aftermath of such disasters; the many casualties and loss of life not to mention the devastation and destruction that is left behind. One critical question that is apparent in such situations is that irrespective of warnings of the eminent threats, why have countries not been prepared and ready to exhibit effective and efficient crisis management and how can we address this moving forward? This chapter tries to answer this question and suggests that by applying the tools, techniques and processes of the knowledge economy to develop a prescriptive model to support superior decision making and better context awareness in E&DS contexts it is possible to be better prepared and ready as well as enable effective and efficient crisis management.

Keywords Crisis management · Emergency and disaster situations · Data mining · Business intelligence · Knowledge management · Knowledge economy · Boyd · OODA loop

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1 Introduction

COVID-19 first surfaced in December 2019 in Wuhan, China. It was not until March 2020 that the World Health Organization (WHO) classified it as a pandemic [33]. The virus is well adapted to human cell receptors, enabling it to easily infect people with an R0 of approximately 2.2 [6]. COVID-19 causes severe respiratory issues which can develop into pneumonia with older adults and people with underlying medical conditions being at higher risk for serious illness requiring oxygen or ventilator assisted breathing [5].

2020 and now 2021 are being dominated by the COVID-19 global pandemic that has affected everyone, some countries more than others. Not only have healthcare systems been challenged but the economic impacts have been significant and will continue to have far reaching implications for several years to come. Scrutiny of how the COVID-19 pandemic has been handled through 2020 indicates that the poor information flow both within and among organizations/agencies involved in preparation for- and management of this emergency and disaster scenario is a key factor and has led to failures whose costs have reached millions of dollars and thousands of unnecessarily lost lives.

Generally, insufficient information distribution is the result of human error, inferior or non-existing interoperability of information systems, inter-agency conflicts and political considerations. This chapter proffers a new approach to emergency and disaster management such as the COVID-19 pandemic grounded in information/knowledge needs based on the combination of the doctrine of *n*etwork-centric *o*perations, the techniques of *k*n*o*wledge *m*anagement and the tools of *i*nformation *s*ystems, NOKOMIS framework. The presented framework provides appropriate guidance and support for decision making in real time, facilities the flow of factual information and knowledge among *all* stakeholders, and assists in the elimination of rumour as a factor in decision making. Thus, the combination of NCO (Network Centric Operations) and KM (Knowledge Management) and Information Systems (IS) provides the core platform for adaptive management and leadership in the context of a superior approach to emergency and disaster management.

2 Description of Model

COVID-19 like any Emergency and Disaster Scenario (E&DS) requires effective crisis management capability, i.e., pre-hospital and emergency/trauma in-hospital medical services, firefighting, disaster-related law enforcement operations, border control etc. and superior decision making capabilities if the crisis is to be at best averted or at least contained [15, 38, 29]. Most of these services are governed by different local or national agencies, are subject to different rules and regulations, and develop independent operational plans [38]. This in turn leads to the gathering and storing of data in disparate databases [29]. However, given the interdependent nature of these elements, any decision making based on only one or a few of these data elements will logically provide at best only a partial picture and thus an inferior decision. Hence, it is necessary to collect multi-spectral data, analyze this data in aggregate to develop a complete picture in order to support superior decisions [29]. To do this effectively and efficiently it is imperative embrace the tools, techniques and processes of the knowledge economy [15, 29, 31, 32] and industry 4.0 [17].

To understand and fully appreciate the key tools, techniques and processes of the knowledge economy, it is necessary first to understand the socio-technical aspects of knowledge management.

2.1 Technical Aspects

The technical aspects of knowledge management are generally addressed within the areas of data mining, analytics and more recently artificial intelligence and machine learning [17, 24, 25].

Due to the immense size of the data sets today, computerized techniques are essential to help decision makers understand relationships and associations between data elements. Data mining is closely associated with databases and shares some common ground with statistics since both strive toward discovering structure in data [7, 10]. However, while statistical analysis starts with some kind of hypothesis about the data, data mining does not (ibid). Furthermore, data mining is much more suited to deal with heterogeneous databases, data sets and data fields, which are typical of data in E&DS that contain numerous types of text and graphical data sets [29]. Data mining also draws heavily from many other disciplines, most notably machine learning, artificial intelligence, and database technology and in today's world of Industry 4.0 is considered is considered its essential enabler [10].

Related to data mining is another key technical aspect data analytics which essentially is the science of analyzing raw data in order to make conclusions about that information [10]. Given the advances in digital technologies, many of the techniques and processes of data analytics today have been automated into mechanical processes and algorithms and thus are able to rapidly analyze large and disparate volumes of data (ibid).

Artificial Intelligence (AI) and Machine Learning (ML) have been applied in diverse industries such as manufacturing, agriculture and healthcare to improve performance of processes, reducing the downtime of machine, and by improving predictability [14, 17]. AI/ML methods and technologies have made machines capable of making decisions with reasoning similar to humans while also maintaining objectivity [11]. Moreover, the wider adoption of AI-based technology and the increased volume of real-world data captured from multiple sources such as IoT devices, wearables, sensors, and other measurement devices [11] contributes to the development of data-driven models which helped better and expeditious decision making vital in E&DS scenarios.

2.2 People Aspects

To best understand the people or socio aspects, it is necessary to understand underlying concepts within the field of knowledge management [24, 25]. In particular that knowledge has different structures and can be tacit (or experiential in someone's head) or explicit (or factual and recorded) [18, 19, 20]. From the stand point of E&DS what is relevant is that factual knowledge and tacit or experiential knowledge must be combined and often extrapolated from a different and distinct context into the current E&DS scenario [15, 38, 25, 29]. It is this rapid and continuous extraction that requires in addition to the technical and people perspective and appreciation of Boyd's OODA Loop and a process perspective.

2.3 Boyd's OODA Loop

A process centric perspective not only combines the essentials of both the people centric and technology centric aspects but of equal importance it also emphasizes the dynamic and on-going nature of the process. This is particularly important in E&DS which are always dynamic and rapidly changing. This process centered perspective is grounded in the original work of Boyd and his OODA Loop; a conceptual framework that maps out the critical process required to support rapid decision making and extraction of critical and germane knowledge [26]. While Boyd's focus was on the art of air warfare and the need to develop situational awareness, assess the options available and make the critical decision to remaining airborne while the enemy became embedded in the terrain below, this maps very well into E&DS in which the fight is again typically a natural protagonist such as fire, flood or a virus [15, 38, 25, 26, 30].

To summarize, the OODA Loop is based on a cycle of four interrelated stages essential to support critical analysis and rapid decision making that revolve in both time and space: Observation followed by Orientation, then by Decision, and finally Action (OODA). At the Observation and Orientation stages, implicit and explicit inputs are gathered or extracted from the environment (Observation) and converted into coherent information (Orientation) [26, 30]. The latter determines the sequential determination (knowledge generation) and Action (practical implementation of knowledge) steps (ibid). The outcome of the Action stage then in turn, affects the starting point (Observation) of the next revolution in the forward progression of the rolling loop (ibid) (Fig. 1).

This process centric perspective also supports a network centric focus [38] that enables heightened situational awareness which will assist in being prepared and ready [29]. The concept of networks as the informational backbone for complex, time-dependent operations performed in unpredictably evolving environments is not new (ibid). In fact, network centric operations have been created and developed and used effectively in the US Department of Defense [1]. Moreover, the network-centric concept evolved into one of the cornerstones of the transformation philosophy

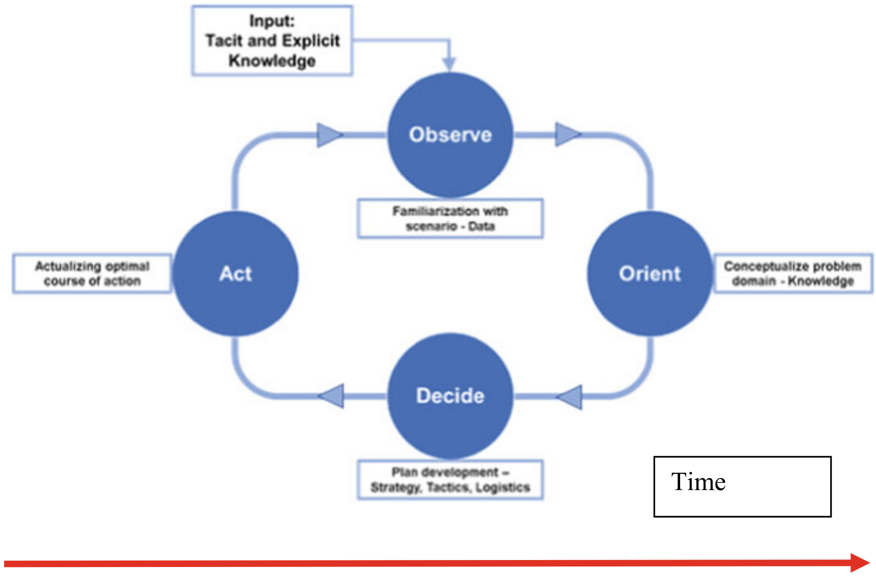

Fig. 1 The OODA loop adapted from [27]

embraced by the Department of Defence [9]. Accordingly, as noted by von Lubitz and Wickramasinghe [15], implementation of network-centric principles in operations allows timely, unhindered sharing of data, information, and knowledge among applications, platforms, and users that is independent of time, technology, and user boundaries, which will result in improved situational awareness and not only significant reduction of decision-making cycles, but contemporaneously more optimal decision making will ensue. Clearly of paramount importance in E&DS.

2.4 The Intelligence Continuum

The Intelligence Continuum consists of the unified collection of key tools, techniques and processes of the knowledge economy; i.e. including data mining, business intelligence/analytics and knowledge management which are applied to a generic system of people, process and technology in a systematic and ordered fashion [27, 30]. Taken together they represent a very powerful instrument for refining the large, voluminous and multispectral raw and often disparate data stored in data marts and/or data warehouses and thereby serve to maximize the value and utility of these data assets. As depicted in Fig. 2 the intelligence continuum is applied to the output of the generic information system. Once applied, the results become part of the data set that are reintroduced into the system and combined with the other inputs of people, processes, and technology to develop an improvement continuum (ibid). Thus, the intelligence

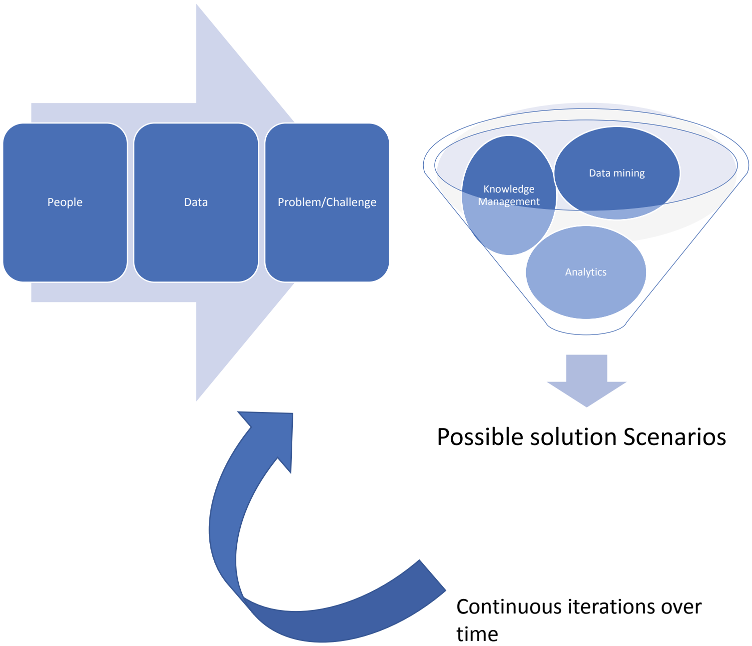

Fig. 2 The intelligence continuum adapted from [27]

continuum includes the generation of data, the analysis of these data to provide a "diagnosis" and the reintroduction into the cycle as a "prescriptive" solution.

The key capabilities and power of the Intelligence Continuum are in analyzing large volumes of disparate, multi-spectral data so that superior decision making can ensue. This is achieved through the incorporation of the various intelligence tools and techniques which taken together make it possible to analyze all data elements in aggregate (ibid). In addition to the ability to analyze large volumes of multi-spectral data the model emphasizes the need for the interaction with people, domain experts. When we apply such a systematic and structured approach as the intelligence continuum affords to a specific E&DS scenario it will be possible to effect superior consequent management.

It is important to note that E&DS scenarios are concomitant with complex, unstable and unpredictable environments where the unknown or position of information inferiority prevails. Hence, such scenarios are typically chaotic, and sub-optimal decision making results. By leveraging the tools and techniques of the intelligence continuum it becomes possible to transform the situation of information inferiority to one of information superiority in real time through the effective and efficient processing of disparate, diverse and seemingly unrelated data. This will then enable decision makers to make superior decisions and chaos will be lessened and order restored.

3 A Possible Network Solution for Better Pandemic Preparedness and Readiness

In April 2020**,** The WHO together with its members established the GOARN [8] (GLOBAL OUTBREAK ALERT AND RESPONSE NETWORK). This collaboration includes institutions and networks around the world that are alert and ready to respond to public health threats. Further, this network combines stakeholder resources to help rapidly identify, confirm, and respond to outbreaks of international importance [33, 34]. GOARN's alliance of technical partner institutions are supported by an oversight steering committee and operational support team based at WHO headquarters [36]. These technical and operational resources come from scientific institutions in WHO member states, medical and surveillance initiatives, lab networks, technical networks, United Nations organizations, and non-governmental organizations (e.g. Red Cross and MSF) [33, 35]. Incorporating into GOARN, a global pandemic surveillance and response information system would complement GOARN's established network of partners, mission, and technical expertise (Fig. 3; [12]).

Such an expansive information system could expand the network of systems already monitored by GOARN such as the Global Public Health Intelligence Network (GPHIN) in Canada or The WHO's Global Influenza Surveillance and Response System (GISRS). GPHIN is an early warning system that monitors printed media reports and the Internet for potential public health threats worldwide including chemical, biological, radiological and nuclear [22]. The GISRS was established as a global surveillance mechanism to improve preparedness and response to support seasonal, pandemic and zoonotic influenza [37]. Data from these types of systems could potentially provide early detection of likely pandemic threats and help monitor public

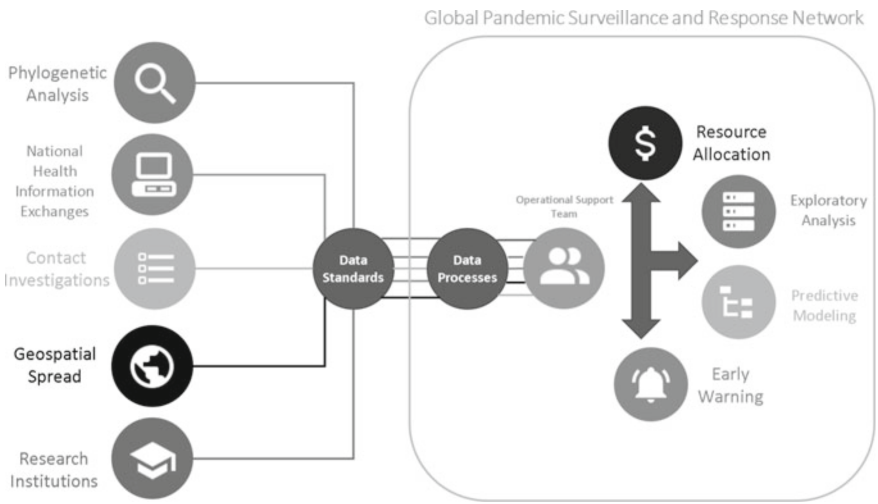

Fig. 3 Data flow for a proposed global pandemic surveillance and response network [12]

health responses to outbreaks. A critical aspect would be to established procedures and standards that can help alleviate interoperability problems before an outbreak occurs and is important for data collection for outbreak investigations [23]. This network system realizes a network centric approach as discussed above underpinned by OODA Loop principles.

Clearly such a network of systems would be able to collect massive quantities of varied data that arrive essentially in real time and at high frequency and includes types of data such as disease surveillance and population health management. By applying the Intelligence Continuum to these data, it would be possible to then produce evidence based recommendations quickly. This in turn would enable large datasets to be suitable for exploratory data analysis and machine learning algorithms. Unsupervised learning algorithms could provide early detection and warning of outbreaks provide greater chances to eliminate spread of a disease and establish a better state or both preparedness and readiness [4]. In addition, during an outbreak, data from geospatial spread monitoring, phylogenetic analysis of an organism, contact investigations, national health information exchanges, and research coming from partner institutions are some examples of data that would flow into this system (see Fig. 3).

As discussed in Sect. 2, facilitation of this type of system (the proposed a global pandemic surveillance and response information system), requires the consideration of adopting a network-centric perspective. Adopting such a perspective ensures a world health information grid infrastructure could be established so that maximum monitoring of the spread and change in the spread of the disease can be detected as early as possible. A system designed for this type of approach can be a powerful tool to improve public health policy and decision-making [4].

Additionally, as noted by Wickramasinghe and Schaffer [28] noted to be successful with such transformative systems it is also necessary to establish the appropriate standardization policies, protocols, and procedures. However, once this has been established, the proposed system would enable better preparedness and readiness with respect to future E&DS especially pandemics.

There are many challenges to the creation, implementation, and adoption of this type of a global pandemic surveillance and response information system. In addition to the need for data standards and procedures already mentioned, providing incentives to conform to new data standards to facilitate information sharing among the many partners will be a challenge. Another large set of barriers to such a system includes the consent, privacy, and information security policies of the system. While many countries have national health care systems in place, they each have separate laws and regulations regarding privacy. While there exist technology solutions such as data aggregation and anonymization, distributed data networks, and blockchain technology for securing the information [4], it will be difficult to get all countries to easily come on board.

4 Discussion

Irrespective of the E&DS, the development of preparedness and readiness, the management of the disaster itself and the subsequent mitigation of its consequences involve a series of steps and tasks which fall into four key phases of prevent, protect, respond and then recover [38]. The current COVID 19 pandemic has certainly highlighted failures globally regarding at least the first 3 of these stages. In contrast, sound emergency and disaster management requires the ability to follow seven key principles [2, 3, 16, 25]:

1. Focus on solvable problems
2. Priorities the elements of a problem in terms of how much progress can be achieved with each element in a small amount of time
3. Delegate responsibility
4. Manage the "span of control"
5. Communicate clearly and rationally
6. Keep a level head in a crisis
7. Make sound decisions

To do this, we need multi-spectral data, pertinent information and germane knowledge.

This chapter has set out how we might be better prepared and ready by incorporating the tools, techniques and technologies of the knowledge economy. In particular, it has served to highlight the importance of taking a socio-technical perspective coupled with a network centric focus assisted with Boyd's OODA Loop and the Intelligence continuum. In Sect. 3 a global pandemic surveillance system was proffered, and while this might seem unatonable at first development, it behooves us all to attempt to realise even parts of this solution to enable us to facilitate a better state of preparedness and readiness a priori so that ex ante operations can in fact be more effective and efficient, decision making superior and order replace much of the chaos.

While many regions and countries were severely impacted by the COVID pandemic, health organizations focused on working to create solutions capable of eliminating the repeat of key errors. These solutions would optimally result in controlling or minimizing the rapid spread of the disease. While COVID-19 impacted different countries at various points in time, a number of ineffective responses were repeated in many countries and resulted in unfortunate outcomes [21]. The recurrence of similar patterns was additional proof that oversights occurring systematically in the absorption of meaningful data and establishing effective and timely response had a key role in repeating the same mistakes [21]. Areas that were severely impacted by the disease, experienced systematic errors that led to lack of effective communication and could transfer timely and meaningful information used in the design of effective pandemic response [13].

What this highlights is a failure at multiple levels to follow the above mentioned 7 key principles but also ensure that pertinent information and germane knowledge are of central focus. To do this rapidly, efficiently and effectively it is only possible by utilizing the intelligence continuum. However, a key success factor is an organizing framework that supports extraction of relevant data, pertinent information and germane knowledge, the combination and utilization of these knowledge assets to support rapid, real-time and superior decision making to enact the 7 key principles of E7DS management. This chapter proffers the NOKMIS framework as such an organizing framework that is powered by the intelligence continuum and incorporates OODA thinking.

5 Conclusion

Despite the numerous challenges in designing, implementing, and operating the proposed global pandemic surveillance system proffered it surely is important if by doing so we might avoid a pandemic as devastating as the current COVID-19 pandemic. The key lesson from COVID-19 and other previous pandemics is that infectious organisms and viruses do not recognize country borders and will rapidly spread across the world. Given today we are a globally economy and so inter-connected, it does become important to focus on a network centric global solution to ensure better preparedness and readiness. The benefits of such a system would be shared by all.

This chapter tries to answer this question of how we might be better prepared and ready for pandemics and other E&DS. The answer lies in leveraging the tools, techniques and technologies of our knowledge economy. In addition, a prescriptive model was proffered (Fig. 3) to support superior decision making and better context awareness in E&DS contexts that would make it possible to be better prepared and ready as well as enable effective and efficient crisis management. However, in answering this question, the conclusion leaves several more unanswered questions which must be left to future work; namely, how can we realise such a vision in practice? One key area is the need for collaboration and partnerships between private and public sectors to enable transfer of accurate information as well as co-ordination of effort and leveraging of vital resources.

References

1. Alberts, D.S., Garstka, J.J., Hayes, R.E., Signori, D.A.: Understanding information age warfare. CCRP Press. http://www.dodccrp.org/publications/pdf/Alberts_UIAW.pdf (2001)
2. Alexander, D.: Principles of Emergency Planning and Management. Terra Publishings, London (2002)
3. Alexander, D.: Cognitive mapping as an emergency management training exercise. J. Contingencies Cris. Manag. **12**, 150–159 (2004)

4. Bates, D.W., Heitmueller, A., Kakad, M., Saria, S.: Why policymakers should care about “big data” in healthcare. Health Policy Technol. **7**(2), 211–216 (2018). https://doi.org/10.1016/j.hlpt.2018.04.006
5. CDC: Centers for Disease Control and Prevention [CDC] available at https://www.cdc.gov/accessed Jan 2022. (2020 March 20)
6. Cascella, M., Rajnik, M., Cuomo, A., Dulebohn, S.C., Di Napoli, R.: Features, evaluation and treatment coronavirus (COVID-19). StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK554776/ (2020)
7. Chung, M., Gray, P.: Special section: data mining. J. Manag. Inf. Syst. **16**(1), 11–16 (1999)
8. GOARN: https://extranet.who.int/goarn/ (2020). Accessed May 2021
9. Garstka, J.J.: Implementation of network centric warfare. Force Transformation Trends. http://www.oft.osd.mil (2004)
10. Geng, H. (ed.): Internet of Things and Data Analytics Handbook. Wiley, New York (2016)
11. Jayaraman, P.P., Forkan, A.R.M., Morshed, A., Haghighi, P.D., Kang, Y.B.: Healthcare 4.0: a review of frontiers in digital health. Wiley Interdiscip. Rev.: Data Min. Knowl. Discov. **10**(2), e1350 (2020)
12. Jolly, J.: Public health information and pandemics: how a global pandemic surveillance and response information system could improve global health security. Unpublished White Paper Report, University of Illinois (2020)
13. Lee, A., Morling, J.: COVID 19: the need for public health in a time of emergency. Elsevier Public Health Emerg. Collect. **182**, 188–189 (2020)
14. Lee, S.M., Lee, D., Kim, Y.S.: The quality management ecosystem for predictive maintenance in the Industry 4.0 era. Int. J. Qual. Innov. **5**(1), 1–11 (2019)
15. von Lubitz, D., Wickramasinghe, N.: Creating germane knowledge in dynamic environments. Int. J. Innov. Learn. **3**(3), 326–347 (2006)
16. Marincioni, F.: A cross-culture analysis of natural disaster response: the Northwest Italy floods of 1994 compared to the U.S. Midwest floods 1993. Int. J. Mass Emergencies Disasters **19**(2), 209–236 (2001)
17. Munirathinam, S.: Industry 4.0: industrial internet of things (IIOT). In: Advances in Computers, vol. 117, pp. 129–164. Elsevier (2020)
18. Newell, S., Robertson, M., Scarbrough, H., Swan, J.: Managing Knowledge Work. Palgrave, New York (2002)
19. Nonaka, I.: A dynamic theory of organizational knowledge creation. Organ. Sci. **5**, 14–37 (1994)
20. Nonaka, I., Nishiguchi, T.: Knowledge Emergence. Oxford University Press, Oxford (2001)
21. Pisano, G.P., Sadun, R., Zanini, M.: Lessons from Italy’s response to coronavirus. Harvard Business Review (2020)
22. Public Health Agency of Canada: About GPHIN. https://gphin.canada.ca/cepr/aboutgphin-rmispenbref.jsp?language=en_CA
23. Silenou, B.C., Tom-Aba, D., Adeoye, O., Arinze, C.C., Oyiri, F., Suleman, A.K.,... Krause, G.: Use of surveillance outbreak response management and analysis system for human monkeypox outbreak, Nigeria, 2017–2019. Emerg. Infect. Dis. **26**(2), 345–349 (2020). https://doi.org/10.3201/eid2602.191139
24. Wickramasinghe, N.: Knowledge creation: a meta-framework. Int. J. Innov. Learn. **3**(5), 558–573 (2006)
25. Wickramasinghe, N., Bali, R.: Controlling chaos through the application of smart technologies and intelligent techniques. Int. J. Risk Assess. Manag. **10**(1–2), 172–182 (2008)
26. Wickramasinghe, N., Bali, R., Gibbons, C., Choi, C., Schaffer, J.: Optimization of healthcare operations with knowledge management. JHIMS Summer **3**(4), 44–50 (2009)
27. Wickramasinghe, N., Schaffer, J.: Creating knowledge driven healthcare processes with the intelligence continuum. Int. J. Electron. Healthc. **2**(2), 164–174 (2006)
28. Wickramasinghe, N., Schaffer, J.: Realizing value driven eHealth solutions. IBM Business of Government. http://www.businessofgovernment.org/sites/default/files/Realizing%20Value%20Driven%20e-Health%20Solutions.pdf (2010)

29. Wickramasinghe, N., Bali, R., Naguib, R.: Application of knowledge management and the intelligence continuum for medical emergencies and disaster scenarios. In: IEEE 2006 International Conference of the Engineering in Medicine and Biology Society (2006)
30. Wickramasinghe, N., Choi, J., Schaffer, J.: Embracing the principles of knowledge management to structure a superior IT healthcare paradigm. In: Wickramasinghe, N., Schaffer, J. (eds.) Theories to Inform Superior Health Informatics Research and Practice, pp. 323–336 (2018)
31. Wigg, K.: Knowledge Management Foundations. Schema Press, Arlington (1993)
32. Wilcox, L.: Knowledge-based systems as an integrating process. In: Liebowitz, J., Wilcox, L. (eds.) Knowledge Management and its Integrative Elements. CRC Press, New York
33. World Health Organization: Global outbreak and response network. https://www.who.int/ihr/alert_and_response/outbreak-network/en/
34. World Health Organization: Global outbreak alert and response. Report of a WHO meeting. https://www.who.int/csr/resources/publications/surveillance/whocdscsr2003.pdf (2000)
35. World Health Organization: Global influenza surveillance & response system. https://www.who.int/influenza/gisrs_laboratory/updates/GISRS_one_pager_2018_EN.pdf (2018)
36. World Health Organization: WHO Director-General's opening remarks at the media briefing on COVID-19. https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020 (2020, March 11)
37. World Health Organization: Virus origin / reducing animal-human transmission of emerging pathogens. https://www.who.int/health-topics/coronavirus/who-recommendations-to-reduce-risk-of-transmission-of-emerging-pathogens-from-animals-to-humans-in-live-animal-markets (2020, March 26)
38. von Lubitz, D., Carrasco, B., Fausone, C., Gabbrielli, F., Kirk, J., Lary, M., Levine, H.: Bioterrorism, medical readiness, and distributed simulation training of first responders. In: Johnson, J., Cwiek, M., Ludlow, G. (eds.) Community and Response to Terrorism (Vol. II): A Community of Organizations: Responsibilities and Collaboration Among All Sectors of Society, pp. 267–312. Praeger (Greenwood Publ. Group), Westport, CT (2005)

mHealth Systems and Applications in Post-pandemic Healthcare

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Abstract The prolonged duration of COVID-19 has caused an unprecedented strain on the healthcare systems to provide necessary treatment and care to COVID-19 infected patients and other existing chronic disease patients with varying severity. With no well-defined preventive and curative treatment available for COVID-19 yet globally, the local and national levels enforced restrictions termed lockdowns with differing magnitude. For the government to ease the lockdown restrictions, healthcare authorities need to identify an infected person and those who came in contact with them to stop the spread of the infection, and for this purpose, federal governments developed contact tracing smartphone applications (apps) to be used by people in that country. In this chapter, we discuss the available contact tracing apps and their technical specifications. Several mobile health (mHealth) apps to address the healthcare needs rising as an outcome of the pandemic are developed, and this chapter gives an overview of a few pandemic driven systems. Finally, the chapter discusses the opportunities and challenges mHealth systems possess to consider for effective, long-lasting implementation.

Keywords Contact tracing apps · Pandemic driven apps · Technology acceptance · mHealth opportunities · mHealth challenges

1 Introduction

COVID-19 is a contagious respiratory tract infection with varying symptom severity ranging from a mild common cold-like illness to severe viral pneumonia, which could lead to acute respiratory distress syndrome that is potentially fatal [1]. Moreover, the risk of mortality due to COVID-19 is high amongst elderly and adults living with chronic conditions such as cardiovascular disease (CVD), diabetes, asthma, and others [2, 3]. Nevertheless, to curb the spread of the virus globally, the national and

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local governments have taken various precautionary measures, including isolations at homes, travel restrictions, and various rigorous quarantine methods [4]. However, although countries are rolling out several vaccinations prioritising high-risk individuals, the emergence of new strains of COVID-19 and slackness in vaccination challenges the return to normality, i.e., a return to pre-pandemic lifestyle [5, 6].

Globally, with uncertainties surrounding spontaneous outbreaks, rapid-widespread infection, and the emergence of new strains, educational institutions and organisations are encouraging their students and employees to undertake their day-to-day tasks from home, resulting in prolonged confinement of many at home [7–9]. In contrast, staying at home restrictions alone might not play a significant role in curbing the spread of COVID-19 but could cause several long-lasting emotional, physical, and medical distress due to the drastically reduced physical activities and restrictions in socialisation [10]. Worryingly, although many individuals never develop symptoms, i.e., asymptomatic, they are 75% as infectious as those who develop symptoms [11]. However, irrespective of an individual being symptomatic or asymptomatic with infection, household dwellers and close contacts are subjected to a higher risk of infectivity [12].

The mHealth technology is an essential tool in improving healthcare provision during the current pandemic [13]. The World Health Organization (WHO) Global Observatory for eHealth defines mHealth as medical and public health practice supported by mobile devices and integrated technologies, including communication systems and peripheral devices [14]. Moreover, with an increase in mobile phone ownership globally in recent years [15], mHealth is finding widespread healthcare applications, including clinical diagnostics, treatment advice, and remote patient monitoring, offering preventive and curative medication to identify, monitor, and manage many globally prevalent chronic diseases [16]. Furthermore, the advancement of embedded sensors in mobile devices, the growing mobile device market globally, advanced communications systems and protocols, and the development of apps, collectively considered, and the awareness of chronic diseases and the challenges posed by the pandemic are an impetus for disruptive mHealth technology development [17].

Globally, to mitigate COVID-19 transmission, contact tracing, which aims to interrupt chains of infection transmission (e.g., through quarantining contacts), has formed part of the response and the effectiveness depends on timely detection and isolation of index cases [18]. Several methods, including apps, are used in contact tracing and with frequent recurring outbreaks globally, contact tracing could play a vital role in containing the spread of the virus until the development of a comprehensive solution to overcome the pandemic. Also, the pandemic has facilitated the development of several apps to monitor individual's health and wellbeing, and the health practitioners could rely on these systems henceforth to deliver care to their patients. Hence, this chapter discusses the functionalities and features of a few contact tracing apps and other pandemic-driven health apps developed and deployed during the pandemic. Furthermore, this chapter outlines the importance of technology acceptance and the opportunities and challenges of mHealth systems.

2 Contact Tracing Apps

Contact tracing plays a significant role in the public health surveillance system to mitigate the spread of the infection and curb mortality, and effectively identify individuals who had come in contact with an infected individual and proactively took protective and preventive measures resulting in COVID-19 related mortality reduction [19]. This section presents few contact tracing apps available from different countries and their features, and Table 1 shows the details of the apps.

Contact tracing apps are developed by national government organisations or by other organisations and supported by federal governments [20]. Moreover, the apps are launched and used by the public in developed and developing countries. However, although many users use the app, the percentage of penetration varies according to the country's population. For example, the population of India is high, and although 163,000,000 users are using the app, it just constitutes 12.05% of the population. At the same time, 4,511,200 users in Singapore represents 80% of the population using the app. Hence, to harness the benefits of contact tracing apps, the national government and public health departments shall take the utmost effort in promoting the app use amongst the population.

The apps have notification features to automatically let users and public health officials know if somebody has potentially been exposed to a covid-19 infected individual. Additionally, the apps used various technologies to effectively identify the contacts in proximity with a COVID-19 infected individual. Most apps used Bluetooth to swap encrypted tokens with any other nearby phones over Bluetooth to capture the individuals within the proximity [20]. Whereas, a few apps used location tracking, i.e., identifying a person's contacts by tracking the phone's movements, using Global Positioning System or triangulation from nearby cell towers and looking for other phones that have spent time in the exact location [20]. Furthermore, many apps rely on the joint Application Programming Interface that Apple and Google are developing, enabling Apple (running iOS operating system (OS)) and phones using Android OS developed by Google to communicate with each other over Bluetooth, allowing developers to build a contact tracing app that will work for both the operating system [20]. Finally, apps used decentralized privacy-preserving proximity tracing (DP-3T), an open-source protocol for Bluetooth-based tracking in which an individual phone's contact logs are stored locally, denying others from knowing those exposed [20].

The apps were free to be downloaded from Google Play Store (Android OS) and App Store (iOS); however, while the use of contact tracing apps is optional in many countries, it is mandatory to use it in a few countries. Moreover, while the primary objective of using the data captured through the app is for contact tracing, there is a possibility for the data to be used for other purposes, such as law enforcement by federal agencies. Furthermore, the captured data availability duration varied, i.e., how long the data is available to be accessed and analysed. For example, a few apps automatically deleted the captured data in a reasonable amount of time, usually a maximum of around 30 days, whereas other apps allow users to delete their data

Table 1 Contact tracing apps available in different countries adapted from [20]

Country	App name	Users	Penetration (%)	Technology	Voluntary	Limited	Data destruction	Minimised	Transparent	Status
Algeria	Algeria's App	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	Launched
Australia	COVIDSafe	7,160,909	28.64	Bluetooth	Y	Y	Y	Y	Y	Launched
Austria	Stopp Corona	600,000	6.77	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Bahrain	BeAware	400,000	25.49	Bluetooth, Location	Y	Y	TBD	N	N	Launched
Bangladesh	Corona Tracer BD	500,000	0.3	Bluetooth, GPS	Y	Y	N	N	TBD	Launched
Belgium	Coronalert	970,000	8.37	Bluetooth, Google/Apple, DP3T	Y	Y	Y	Y	Y	Launched
Bulgaria	ViruSafe	55,000	0.79	Location	Y	Y	Y	N	Y	Launched
Canada	COVID Alert	5,314,026	14.03	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
China	Chinese health code system	TBD	TBD	Location, Data mining	N	N	N	N	N	Launched
Cyprus	CovTracer	9,000	0.77	Location	Y	N	Y	Y	Y	Launched
Czech Republic	eRouska	240,000	2.25	Bluetooth	Y	Y	Y	Y	Y	Launched
Denmark	Smittelstop	619,000	10.69	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched

(continued)

Table 1 (continued)

Country	App name	Users	Penetration (%)	Technology	Voluntary	Limited	Data destruction	Minimised	Transparent	Status
Estonia	HOIA	250,944	18.88	Bluetooth, DP-3T, Google/Apple	Y	TBD	TBD	Y	Y	Launched
Fiji	CareFiji	27,000	3.06	Bluetooth	Y	TBD	TBD	Y	Y	Launched
Finland	Koronavilkku	2,500,000	45.31	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
France	TousAntiCovid	2,400,000	3.58	Bluetooth	Y	Y	Y	Y	Y	Re-launched
Germany	Corona-Warn-App	18,000,000	21.68	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Ghana	GH COVID-19 Tracker	TBD	TBD	Location	Y	N	TBD	N	N	Launched
Gibraltar	Beat Covid Gibraltar	9,000	26.69	Bluetooth	Y	Y	Y	Y	Y	Launched
Hungary	VirusRadar	35,000	0.36	Bluetooth	Y	TBD	Y	Y	Y	Launched
Iceland	Rakning C-19	140,000	38.45	Location	Y	Y	Y	Y	Y	Launched
India	Aarogya Setu	163,000,000	12.05	Bluetooth, Location	N	Y	Y	N	N	Launched
Indonesia	PeduliLindungi	4,600,000	1.72	Bluetooth, Location	Y	N	N	N	N	Launched
Iran	AC19	0	0.00	NA	N	N	N	N	N	Launched
Ireland	Covid Tracker	1,300,000	26.33	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Israel	HaMagen 2.0	2,000,000	22.51	Location	N	Y	Y	Y	Y	Launched

(continued)

Table 1 (continued)

Country	App name	Users	Penetration (%)	Technology	Voluntary	Limited	Data destruction	Minimised	Transparent	Status
Italy	Immuni	9,769,449	16.19	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Japan	COCOA	7,700,000	6.09	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Kuwait	Shlonik	TBD	TBD	Location	Y	TBD	N	N	N	Launched
Malaysia	MyTrace	100,000	0.32	Bluetooth	Y	N	Y	N	N	Launched
Mexico	CovidRadar	50,000	0.04	Bluetooth	Y	N	N	N	N	Launched
New Zealand	NZ COVID Tracer	605,751	12.45	Bluetooth, QR codes, Google/Apple	Y	Y	Y	N	Y	Launched
North Macedonia	StopKorona	TBD	TBD	Bluetooth	Y	Y	Y	Y	Y	Launched
Northern Ireland	StopCOVID NI	TBD	TBD	Bluetooth, Google/Apple	Y	TBD	TBD	TBD	TBD	Launched
Norway	Smittestopp	158,000	2.94	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Philippines	StaySafe	2,000,000	1.87	Bluetooth	Y	N	N	N	N	Launched
Poland	ProteGO Safe	725,000	1.91	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Qatar	Ehteraz	2,531,620	91.00	Bluetooth, Location	N	TBD	N	N	N	Launched
Saudi Arabia	Tawakkalna	7,000,000	20.77	Location	Y	N	Y	N	N	Launched

(continued)

Table 1 (continued)

Country	App name	Users	Penetration (%)	Technology	Voluntary	Limited	Data destruction	Minimised	Transparent	Status
Saudi Arabia	Tabaud	TBD	TBD	Bluetooth, Google/Apple	Y	Y	Y	Y	N	Launched
Singapore	TraceTogether	4,511,200	80.00	Bluetooth, BlueTrace	N	N	Y	N	Y	Launched
South Africa	COVID Alert SA	600,000	1.0	Bluetooth, Google/Apple	Y	Y	Y	Y	TBD	Launched
Switzerland	SwissCovid	1,600,000	18.67	Bluetooth, DP-3T, Google/Apple	Y	Y	Y	Y	Y	Launched
Thailand	MorChana	3,690,000	53.15	Bluetooth, Location	Y	TBD	TBD	N	N	Launched
Tunisia	E7mi	23,140	0.20	Bluetooth	Y	Y	Y	N	N	Launched
Turkey	Hayat Eve Sığar	14,186,000	17.30	Bluetooth, Location	N	N	N	Y	N	Launched
UAE	TraceCovid	TBD	TBD	Bluetooth	N	TBD	TBD	Y	N	Launched
UK	NHS COVID-19 App	19,000,000	28.51	Bluetooth, Google/Apple	Y	Y	Y	Y	Y	Launched
Vietnam	BlueZone	20,000,000	20.93	Bluetooth	Y	Y	N	N	Y	Launched

TBD: To be determined, Y: Yes, N: No, UAE: United Arab Empire, UK: United Kingdom manually, and a few apps did not have the option to delete the captured data. Besides, most of the apps precisely collected data necessary for the contact tracing purpose, but a few apps failed to collect minimised information. Additionally, the transparency determined if the developed apps were transparent, taking clear, publicly available policies and design and an open-source code base.

3 Pandemic Driven Health Apps

The prolonged duration individuals are spending at home due to various COVID-19 restrictions is causing several long-lasting emotional, physical, and medical distress due to the drastically reduced physical activities and restrictions in socialisation [10]. Moreover, chronic disease patients are dependent on healthcare systems life-long that involves different stakeholders, including healthcare professionals, specialised healthcare centres, primary healthcare providers, and community-based services [16, 21]. However, COVID-19 local and global travel restrictions and hospital access policies have limited access to hospital care for chronic disease patients, created uncertainty over their disease status, accentuated their emotional situation, and aggravated their medical condition [22]. Consequently, COVID-19 highlights the imperative need for countries irrespective of their economic levels to ensure an equitable and accessible healthcare system to meet people's emerging healthcare needs, such as easily accessible, affordable, non-discriminant and equitable care, and tailored to the individual's needs [23].

To assist individuals in self-management of their health and wellbeing and monitor the patient's health while at home, several apps are developed globally by governments or national authorities, healthcare organisations, and others drastically during the pandemic [24]. Moreover, the apps adapted methodologies such as surveys, passive monitoring and surveys, and passive monitoring to capture individuals recording according to the objectives of the apps. Accordingly, in this section, we discuss a few mHealth systems developed and deployed after the onset of the pandemic and Table 2 presents the details.

Surveys are a straightforward approach to understand the perception of an individual. Moreover, due to the enforced restrictions and hesitation in visiting hospitals to examine their health, undertaking a survey could present individuals with an appropriate suggestion to seek further medical attention. Furthermore, although apps are a medium to deliver the surveys, the studies have used standard questionnaires that are evaluated and well accepted for the administered objective. Additionally, customised questionnaires were also administered for specific purposes that are evolving currently, for example, evaluating COVID-19 news exposure and COVID-19 perceived threat of death on mental health [25], and work and life pattern changes due to COVID-19 [26]. Moreover, using a questionnaire or a group of collective questionnaires, the studies evaluate the participant's mental health [25, 27], changes in physical activity [28], changes in work and life patterns [26], and emotional intelligence and mindfulness [29].

Table 2 mHealth technologies during COVID-19

Articles	mHealth tool	Age	Objective	Assessed parameters
Survey				
Elhai et al. [25]	App: WeChat	17–64	Mental health	Demographical, DASS-21, GAD-7, SAS-SV, COVID-19 news exposure, COVID-19 perceived threat of death
Yang and Koenigstorfer [28]	PA apps	39.1 (± 10.6)	PA	PA and intention to be PA, app features, PA apps usage, demographics
Zhang et al. [27]	App: WeChat	26–46	Mental health	Demographics, content delivery, questionnaire
Sato et al. [26]	App: CALO Mama	~20–≥60	Changes in work and life patterns	Work and life patterns, depressive symptoms
Sturgill et al. [29]	App: Ajivar	18–29	Emotional intelligence and mindfulness	The TestWell Wellness Inventory, The 9-Item Patient Health Questionnaire, GAD-7
Passive sensing and survey				
Huckins et al. [30]	App: StudentLife	18–22	Mental health	Passive: sedentary, sleep, location, phone usage Survey: COVID-19 news coverage

(continued)

Table 2 (continued)

Articles	mHealth tool	Age	Objective	Assessed parameters
Norbury et al. [31]	App: Evidence-Based Behaviour (eB^2) monitoring	μ:45	Maintenance of PA	Passive: PA AND smartphone use data Survey: Emotional state
Passive sensing				
Sun et al. [32]	RADAR-base App/Fitbit	–	Monitor behavioural changes	Location, PA, sleep, HR, and phone use
Beukenhorst et al. [33]	App: Beiwe	56.6 (± 9.9)	Behavioural changes	GPS sensor for 60 s every 10 min
McCarthy et al. [34]	App: BetterPoints	41 (± 12)	PA behaviour	Walking, running, or cycling
Sañudo et al. [35]	App: Your Hour, Screen Time, Wristband	22.6 (± 3.4)	PA, sedentary behaviour, smartphone use, and sleep patterns	Smartphone usage and wrist band (steps and sleep)

PA: Physical activity, DASS-21: Depression anxiety stress scale-21, GAD-7: Generalized anxiety disorder scale-7, SAS-SV: Smartphone addiction scale-short version, HR: Heart rate

The advancement in smartphone technology enables health and behaviour parameters to be captured passively [17]. In addition to capturing the user perceptions through surveys, the apps had the provision for monitoring other parameters passively [30, 31]. For example, a study to evaluate the participant's mental health surveyed the influence of COVID-19 news coverage and passively monitored its consequences on physical activity, sleep, location, and phone usage [30]. Likewise, another study to observe the influence of physical activity on the emotional state of the individuals surveyed their emotional state and correlated it against the passively captured physical activity and phone usage statistics [31].

A few studies passively monitored the individual's physical activity and day-to-day behavioural patterns such as phone usage [32–35]. In addition to the app's capabilities, studies integrated wearable devices such as Fitbit and wristband to capture additional physical activity and health parameters recording [32, 35]. Moreover, to evaluate the behavioural changes with the severity of COVID-19 over a period, studies analysed the captured recordings.

4 Technology Acceptance

Older adults infected with COVID-19 have severe infection resulting in critical illness and mortality [36]. In addition to the mobility challenges, the severity and restrictions associated with COVID-19 have restricted older adults for a prolonged period in their usual residence. Nevertheless, the minimised physical activity has adverse effects on psychological wellbeing during the pandemic [37]. On the contrary, the considered studies have comparatively younger participants [25–35]. Hence, there is a need to design apps targeting older adults.

The acceptance of mHealth systems amongst end-users can be evaluated by performing usability testing using Technology Acceptance Models in a realistic scenario and environment to evaluate the easiness in use and usefulness of the solution and determine system acceptability [38]. Additionally, addressing the following factors when developing an app targeting older adults could enable the app to receive wider acceptance among them and would be beneficial [39].

Interface design: The interface is the mode through which the user communicates with the app. Hence, having an effective interface is very important to engage users. Accordingly, having a simple and clean interface could be engaging, i.e., an interface not crowded with too much text or information [39]. Moreover, having the texts with visible fonts and sizes could assist older adults to read easily. Additionally, including visual informatics could be of assistance.

Navigation: Navigation options are vital for transiting seamlessly between contents presented in the app. Moreover, having an option to seek help and support regarding the app's features and navigation menus could be of assistance to users [39].

Notifications: Notifications through alerts and reminders encourage app users to proactively use the app for the designated purpose and enhance the user interactions with the app. Moreover, users desire apps with simple notifications by smartphone alerts, text messages, or emails that provide a comprehensive overview of their health goal overview [39]. Preferably, the apps should have the option to let the user have control over the type and frequency of the notifications.

Data collection: The apps methods to capture user information related to their health and wellbeing vary between manual data entry and passive sensing. Moreover, users prefer apps that could passively sense relevant information and, to an extent, those apps that assist them to enter details quickly through visual selection using graphical designs and other options such as clicking and selecting from drop-down menus rather than manually entering.

Goal management: Apps can have options to set goals to assist users to achieve the daily target for their wellbeing. For example, apps considering physical activity as a parameter for the wellbeing of the users could permit them to set goals for their daily steps walked, active time, and other customisable parameters, consequently promoting health and wellbeing [40]. Additionally, apps sending regular notifications about their progress through text messages, push pop-ups, or emails, help users stay motivated and on track with their goals over time [39].

Medication adherence: Among elderly adults, forgetting could be a significant reason for not adhering to their prescribed medication. Apps tended to increase medication adherence by various notification methods [41]. Accordingly, designing and developing apps that could promote medication adherence among the elderly according to their healthcare needs could be of great assistance.

Fit between user and system: Although there are several healthcare apps developed and available for various healthcare needs, apps with a fit between user and system is used by many users and for a long duration, i.e., apps having a good match between user attributes and app attributes [39]. Moreover, when there is a good match between user attributes, such as preferences, expectations, and personality traits and app attributes, such as interface, features, content, navigation, and rules, the apps usage continues beyond the first few interactions [39].

5 Opportunities of mHealth

With mobile subscriptions poised to grow globally [42] and innovation and development of various mHealth systems, mHealth systems could revolutionise the healthcare systems globally, and the following are a few significant opportunities for mHealth systems in healthcare systems.

Equitable healthcare access: Developing countries lack healthcare infrastructure, equipment, easy hospital access, and many other healthcare access challenges [43].

On the other hand, mHealth promises to support public health and clinical care in developing countries with steady growth in chronic diseases and a constant burden from communicable diseases [44]. Nevertheless, although the technology adoption is at a languid pace due to challenges such as inadequate health literacy, cultural and language barrier, lack of skilled medical staff, lack of infrastructure, and economic barriers, the implementation of mHealth technologies in the healthcare system has numerous benefits, including education and awareness, clinical decision support systems, epidemic outbreak tracking, training of healthcare workers, remote monitoring, and many others [45]. Hence, to strengthen the use of technology in the developing countries healthcare systems, it is essential to have strong governance and policies, investment in technology and training to improve acceptability [43].

Patient monitoring at home: Embracing technology in healthcare would assist healthcare workers to be supported digitally and provide healthcare access at the individual's residence [46]. Furthermore, monitoring at an individual's residence opens an avenue to capture multiple physical, medical, and behavioural data non-invasively. Moreover, the option to monitor multiple parameters and capture various data could generate a massive amount of patient health digital data which could be used to deliver personalised healthcare solutions [46].

Decision support systems: The mHealth systems comprising various sensor integrated apps facilitate capturing a vast amount of patient-related data. Moreover, using assistive systems to analyse the vast amount of differing captured data could provide various insights and support healthcare practitioners in treating their patients. Accordingly, decision support systems (DSS) tools aim to improve clinical diagnostic decision-making and patient safety by analysing the patient-generated data and are increasingly prevalent with improvements in mHealth systems [47]. Moreover, the use of DSS tools in healthcare could offer better healthcare services to individuals.

Machine learning: The application of machine learning, a branch of artificial intelligence in patient-generated data, could extract new knowledge that could assist healthcare practitioners in making well-informed decisions to maintain individual's health and wellbeing by providing appropriate healthcare services [48]. Moreover, machine learning has found applications starting from information extraction from medical documents until predicting or diagnosing disease [49]. Additionally, machine learning-based computational decision making is used in patient care, resource allocation, and research on treatments for various diseases [49].

6 Challenges of mHealth

The mHealth systems have several associated opportunities; however, various challenges surround their implementation and utilisation. In this section, we discuss a few challenges.

Implementation: The unprecedented humanitarian and economic needs due to COVID-19 is an impetus to the development and adoption of mHealth technologies at an unprecedented scale and speed; however, since these technologies cannot operate in isolation, there is a need in integrating the technologies seamlessly into existing public healthcare systems [50]. Moreover, infrastructure deficiencies, limited access to Medicare, hospital resources centred in urban areas, and shortage of trained healthcare workers are barriers to equitable healthcare access in developing countries [44, 51]. Consequently, there is a need to revisit the healthcare policy to make suitable adjustments and formulate guidelines to accommodate mHealth systems during the pandemic era and subsequently in longer terms with robust public policy [52].

Open access data: The pandemic triggered an unprecedented growth of collaborative efforts to capture various data and deployment of analysis frameworks; however, while several countries collected clinical data at a national level, these data are restricted to non-government establishments for independent researchers [53]. The availability of data and application of digital technologies for big data analytics, next-generation telecommunication networks and artificial intelligence could assist in the fight against the various issues related to the management and containment of the pandemic and could revolutionise the healthcare system in providing personalised healthcare solutions [53]. Moreover, it is imperative to ensure that the systems are interoperable [53].

Requirement analysis: It has been observed that during the development of ICT based healthcare system, the system developers have minimal interactions with stakeholders of the healthcare system, resulting in the development of inept healthcare systems [51].

Data Privacy: There are concerns about privacy and data protection threat due to the vast amount of data generated through mHealth technologies [54]. There is a need to develop and formulate guidelines for developing mHealth systems to adhere to the collection of optimal data according to the necessity and how it will be stored and used for necessary analysis without compromise in user identity and security breach [54].

Regulation: The revolution in smartphone technologies, direct-to-consumer genetic testing, crowd-sourced information, and big data have enabled researchers, including independent researchers, citizen scientists, patient-directed researchers, do-it-yourself (DIY) researchers, and self-experimenters, in facilitating the development of mHealth systems [55]. On the other hand, the easy access to mHealth systems increases the potential of unregulated health research [55], which could be beneficial but could pose risks to the users such as accuracy, privacy, and safety [56]. Moreover, there is an ambiguity regarding when a medical app could be considered a formal medical device [57]?

COVID-19 has forced the development of various mHealth tools to facilitate information sharing, risk assessment, self-management of symptoms, contact tracing, home monitoring, decision making, and rapidly offering valuable and usable disease monitoring and managing tools [58]. Although mHealth system is vital for epidemic control, mandatory conformance to relevant data privacy regulations is needed to minimise data misuse [59]. Furthermore, apps developed in a country and uploaded to app stores are accessed by individuals from different countries [32, 60, 61]. Hence there is an imperative need for the governments to regulate the development and deployment of mHealth systems through competent regulatory agencies [56, 62].

The apps uploaded in app stores can be downloaded and used by individuals from different countries. The processing of personal data in Europe is regulated by general data protection regulation [63]. However, there is an uncertainty in the governing regulation to be followed when other country users access an app developed in Europe, and there is an ambiguity if data collected by apps are protected by any laws or regulations [64]. Nevertheless, the current pandemic has highlighted the need for standardisation of apps developed following appropriate regulations and guidelines for accessing globally.

Developing countries: The pandemic has shaken developed countries with sophisticated infrastructure, sanitation, and hygiene and developing countries lacking infrastructure, resources, fragile governments, and impoverished communities [65]. However, developing countries are plagued with barriers, such as infrastructure, lack of equipment, technology gap, and many others in deploying mHealth systems effectively and overcoming the barriers could transform the healthcare system globally [43]. Hence, implementing a technology-based system could be at an apathetic pace.

7 Conclusion

The mHealth system with track and trace options are currently an effective tool in contact tracing. Additionally, mHealth systems assist in the health and wellbeing monitoring of individual's during challenging times due to the COVID-19 pandemic. Affirmatively, the increasing mobile phone subscriptions globally and the application of mHealth in various aspects of healthcare suggest that mHealth could significantly affect advancing healthcare during and after the pandemic. However, to realise the mHealth opportunities, the challenges associated with mHealth are to be addressed efficiently, which could take a prolonged duration and needs effective policies and regulations to govern the development and deployment of such systems.

References

1. Bestpractice.bmj.com: Coronavirus disease 2019 (COVID-19). BMJ (updated 13 August 2020; cited 2020 13 August). Available from: https://bestpractice.bmj.com/topics/en-us/3000168 (2020)
2. Williamson, E.J., Walker, A.J., Bhaskaran, K., Bacon, S., Bates, C., Morton, C.E., et al.: Factors associated with COVID-19-related death using OpenSAFELY. Nature **584**(7821), 430–436 (2020)

3. Clark, A., Jit, M., Warren-Gash, C., Guthrie, B., Wang, H.H.X., Mercer, S.W., et al.: Global, regional, and national estimates of the population at increased risk of severe COVID-19 due to underlying health conditions in 2020: a modelling study. Lancet Glob. Health **8**(8), e1003–e1017 (2020)
4. Meo, S.A., Abukhalaf, A.A., Alomar, A.A., AlMutairi, F.J., Usmani, A.M., Klonoff, D.C.: Impact of lockdown on COVID-19 prevalence and mortality during 2020 pandemic: observational analysis of 27 countries. Eur. J. Med. Res. **25**(1), 56 (2020)
5. Fontanet, A., Autran, B., Lina, B., Kieny, M.P., Karim, S.S.A., Sridhar, D.: SARS-CoV-2 variants and ending the COVID-19 pandemic. Lancet **397**(10278), 952–954 (2021)
6. Hossain, M.K., Hassanzadeganroudsari, M., Apostolopoulos, V.: The emergence of new strains of SARS-CoV-2. What does it mean for COVID-19 vaccines? Expert Rev. Vaccines 1–4 (2021)
7. Engzell, P., Frey, A., Verhagen, M.D.: Learning loss due to school closures during the COVID-19 pandemic. Proc. Natl. Acad. Sci. **118**(17), (2021)
8. Lin, C.-Y., Browning, M.H.E.M., Larson, L.R., Sharaievska, I., Rigolon, A., McAnirlin, O., et al.: Psychological impacts from COVID-19 among university students: risk factors across seven states in the United States. Plos One **16**(1), (2021)
9. Vyas, L., Butakhieo, N.: The impact of working from home during COVID-19 on work and life domains: an exploratory study on Hong Kong. Policy Des. Pract. 1–18 (2020)
10. Savaris, R.F., Pumi, G., Dalzochio, J., Kunst, R.: Stay-at-home policy is a case of exception fallacy: an internet-based ecological study. Sci. Rep. **11**(1), 5313 (2021)
11. Johansson, M.A., Quandelacy, T.M., Kada, S., Prasad, P.V., Steele, M., Brooks, J.T., et al.: SARS-CoV-2 transmission from people without COVID-19 symptoms. JAMA Netw. Open **4**(1), e2035057 (2021)
12. Li, F., Li, Y.-Y., Liu, M.-J., Fang, L.-Q., Dean, N.E., Wong, G.W.K., et al.: Household transmission of SARS-CoV-2 and risk factors for susceptibility and infectivity in Wuhan: a retrospective observational study. Lancet Infect. Dis. **21**(5), 617–628 (2021)
13. Monaghesh, E., Hajizadeh, A.: The role of telehealth during COVID-19 outbreak: a systematic review based on current evidence. BMC Public Health **20**(1), 1193 (2020)
14. Who.int: mHealth new horizons for health through mobile technologies. World Health Organization (updated 2011; cited 2021 13 April). Available from: https://www.who.int/goe/publications/goe_mhealth_web.pdf (2011)
15. Rowland, S.P., Fitzgerald, J.E., Holme, T., Powell, J., McGregor, A.: What is the clinical value of mHealth for patients? npj Digit. Med. **3**(1), (2020)
16. Adibi, S.: Introduction. In: Adibi, S. (ed.) Mobile Health. Springer Series in Bio-Neuroinformatics, pp. 1–7 (2015)
17. Baig, M.M., Gholamhosseini, H., Connolly, M.J.: mHealth monitoring system for hospitalised older adults – current issues and challenges. In: Adibi, S. (ed.) Mobile Health. Springer Series in Bio-/Neuroinformatics, pp. 299–317 (2015)
18. Braithwaite, I., Callender, T., Bullock, M., Aldridge, R.W.: Automated and partly automated contact tracing: a systematic review to inform the control of COVID-19. Lancet Digit. Health **2**(11), e607–e621 (2020)
19. Vecino-Ortiz, A.I., Villanueva Congote, J., Zapata Bedoya, S., Cucunuba, Z.M.: Impact of contact tracing on COVID-19 mortality: an impact evaluation using surveillance data from Colombia. PLoS ONE **16**(3), e0246987 (2021)
20. O'Neill, P.H., Ryan-Mosley, T., Johnson, B.: MIT COVID tracing tracker 2020 (updated 16 March 2021). Available from: https://www.technologyreview.com/2020/05/07/1000961/launching-mittr-covid-tracing-tracker/ (2020)
21. De Regge, M., De Pourcq, K., Meijboom, B., Trybou, J., Mortier, E., Eeckloo, K.: The role of hospitals in bridging the care continuum: a systematic review of coordination of care and follow-up for adults with chronic conditions. BMC Health Serv. Res. **17**(1), 550 (2017)
22. Kang, C., Yang, S., Yuan, J., Xu, L., Zhao, X., Yang, J.: Patients with chronic illness urgently need integrated physical and psychological care during the COVID-19 outbreak. Asian J Psychiatr. **51**, 102081 (2020)

23. Nomura, S., Siesjo, V., Tomson, G., Mohr, W., Fukuchi, E., Shibuya, K., et al.: Contributions of information and communications technology to future health systems and Universal Health Coverage: application of Japan's experiences. Health Res. Policy Syst. **18**(1), 73 (2020)
24. Almalki, M., Giannicchi, A.: Health apps for combating COVID-19: descriptive review and taxonomy. JMIR Mhealth Uhealth **9**(3), e24322 (2021)
25. Elhai, J.D., Yang, H., McKay, D., Asmundson, G.J.G.: COVID-19 anxiety symptoms associated with problematic smartphone use severity in Chinese adults. J. Affect. Disord. **274**, 576–582 (2020)
26. Sato, K., Sakata, R., Murayama, C., Yamaguchi, M., Matsuoka, Y., Kondo, N.: Changes in work and life patterns associated with depressive symptoms during the COVID-19 pandemic: an observational study of health app (CALO mama) users. Occup. Environ. Med. (2021)
27. Zhang, Z.D., Zhang, L., Zheng, J.W., Xiao, H., Li, Z.G.: COVID-19-related disruptions and increased mHealth emergency use intention: experience sampling method study. JMIR Mhealth Uhealth **8**(12), (2020)
28. Yang, Y., Koenigstorfer, J.: Determinants of physical activity maintenance during the Covid-19 pandemic: a focus on fitness apps. Transl. Behav. Med. **10**(4), 835–842 (2020)
29. Sturgill, R., Martinasek, M., Schmidt, T., Goyal, R.: A novel artificial intelligence-powered emotional intelligence and mindfulness app (Ajivar) for the college student population during the COVID-19 pandemic: quantitative questionnaire study. JMIR Form. Res. **5**(1), e25372 (2021)
30. Huckins, J.F., daSilva, A.W., Wang, W., Hedlund, E., Rogers, C., Nepal, S.K., et al.: Mental health and behavior of college students during the early phases of the COVID-19 pandemic: longitudinal smartphone and ecological momentary assessment study. J. Med. Internet Res. **22**(6), e20185 (2020)
31. Norbury, A., Liu, S.H., Campaña-Montes, J.J., Romero-Medrano, L., Barrigón, M.L., Smith, E., et al.: Social media and smartphone app use predicts maintenance of physical activity during Covid-19 enforced isolation in psychiatric outpatients. Mol. Psychiatry (2020)
32. Sun, S., Folarin, A.A., Ranjan, Y., Rashid, Z., Conde, P., Stewart, C., et al.: Using smartphones and wearable devices to monitor behavioral changes during COVID-19. J. Med. Internet Res. **22**(9), e19992 (2020)
33. Beukenhorst, A.L., Collins, E., Burke, K.M., Rahman, S.M., Clapp, M., Konanki, S.C., et al.: Smartphone data during the COVID-19 pandemic can quantify behavioral changes in people with ALS. Muscle Nerve **63**(2), 258–262 (2021)
34. McCarthy, H., Potts, H.W.W., Fisher, A.: Physical activity behavior before, during, and after COVID-19 restrictions: longitudinal smartphone-tracking study of adults in the United Kingdom. J. Med. Internet Res. **23**(2), e23701 (2021)
35. Sanudo, B., Fennell, C., Sanchez-Oliver, A.J.: Objectively-assessed physical activity, sedentary behavior, smartphone use, and sleep patterns pre- and during-COVID-19 quarantine in young adults from Spain. Sustainability **12**(15), (2020)
36. Singhal, S., Kumar, P., Singh, S., Saha, S., Dey, A.B.: Clinical features and outcomes of COVID-19 in older adults: a systematic review and meta-analysis. BMC Geriatr. **21**(1), 321 (2021)
37. Jenkins, M., Houge Mackenzie, S., Hodge, K., Hargreaves, E.A., Calverley, J.R., Lee, C.: Physical activity and psychological well-being during the COVID-19 lockdown: relationships with motivational quality and nature contexts. Front Sports Act Living **3**, 637576 (2021)
38. Gerdes, M., Trinugroho, Y.B.D., Næss, M., Fensli, R.: Security, reliability and usability of mHealth environments. In: Adibi, S. (ed.) Mobile Health. Springer Series in Bio-Neuroinformatics, pp. 1043–1066 (2015)
39. Vaghefi, I., Tulu, B.: The continued use of mobile health apps: insights from a longitudinal study. JMIR Mhealth Uhealth **7**(8), e12983 (2019)
40. Baretta, D., Bondaronek, P., Direito, A., Steca, P.: Implementation of the goal-setting components in popular physical activity apps: review and content analysis. Digit Health **5**, 2055207619862706 (2019)

41. Al-Arkee, S., Mason, J., Lane, D.A., Fabritz, L., Chua, W., Haque, M.S., et al.: Mobile apps to improve medication adherence in cardiovascular disease: systematic review and meta-analysis. J. Med. Internet Res. **23**(5), e24190 (2021)
42. Ericsson: Ericsson mobility report. Report No. 1 (2020)
43. Kruse, C., Betancourt, J., Ortiz, S., Valdes Luna, S.M., Bamrah, I.K., Segovia, N.: Barriers to the use of mobile health in improving health outcomes in developing countries: systematic review. J. Med. Internet Res. **21**(10), e13263 (2019)
44. Kahn, J.G., Yang, J.S., Kahn, J.S.: 'Mobile' health needs and opportunities in developing countries. Health Aff. **29**(2), 254–261 (2010)
45. Latif, S., Rana, R., Qadir, J., Ali, A., Imran, M.A., Younis, M.S.: Mobile health in the developing world: review of literature and lessons from a case study. IEEE Access **5**, 11540–11556 (2017)
46. Mitchell, M., Kan, L.: Digital technology and the future of health systems. Health Syst. Reform **5**(2), 113–120 (2019)
47. Patel, R., Green, W., Shahzad, M.W., Larkin, C.: Use of mobile clinical decision support software by junior doctors at a UK teaching hospital: identification and evaluation of barriers to engagement. JMIR Mhealth Uhealth **3**(3), e80 (2015)
48. Sako, Z., Adibi, S., Wickramasinghe, N.: Addressing data accuracy and information integrity in mHealth solutions using machine learning algorithms. In: Wickramasinghe, N., Bodendorf, F. (eds.) Delivering Superior Health and Wellness Management with IoT and Analytics. Healthcare Delivery in the Information Age Ser, pp. 345–359. Springer International Publishing AG (2019)
49. Jayatilake, S., Ganegoda, G.U.: Involvement of machine learning tools in healthcare decision making. J. Healthc. Eng. **2021**, 6679512 (2021)
50. Budd, J., Miller, B.S., Manning, E.M., Lampos, V., Zhuang, M., Edelstein, M., et al.: Digital technologies in the public-health response to COVID-19. Nat. Med. **26**(8), 1183–1192 (2020)
51. Eze, E., Gleasure, R., Heavin, C.: Reviewing mHealth in developing countries: a stakeholder perspective. Procedia Comput. Sci. **100**, 1024–1032 (2016)
52. Lai, J., Widmar, N.O.: Revisiting the digital divide in the COVID-19 era. Appl. Econ. Perspect. Policy (2020)
53. Dagliati, A., Malovini, A., Tibollo, V., Bellazzi, R.: Health informatics and EHR to support clinical research in the COVID-19 pandemic: an overview. Brief Bioinform. **22**(2), 812–822 (2021)
54. Newlands, G., Lutz, C., Tamò-Larrieux, A., Villaronga, E.F., Harasgama, R., Scheitlin, G.: Innovation under pressure: implications for data privacy during the Covid-19 pandemic. Big Data Soc. **7**(2), (2020)
55. Rothstein, M.A., Wilbanks, J.T., Beskow, L.M., Brelsford, K.M., Brothers, K.B., Doerr, M., et al.: Unregulated health research using mobile devices: ethical considerations and policy recommendations. J. Law Med. Ethics **48**(1_suppl), 196–226 (2020)
56. Jogova, M., Shaw, J., Jamieson, T.: The regulatory challenge of mobile health: lessons for Canada. Healthc. Policy **14**(3), 19–28 (2019)
57. Lewis, T.L., Wyatt, J.C.: mHealth and mobile medical apps: a framework to assess risk and promote safer use. J. Med. Internet Res. **16**(9), e210 (2014)
58. Kondylakis, H., Katehakis, D.G., Kouroubali, A., Logothetidis, F., Triantafyllidis, A., Kalamaras, I., et al.: COVID-19 mobile apps: a systematic review of the literature. J. Med. Internet Res. **22**(12), e23170 (2020)
59. Ekong, I., Chukwu, E., Chukwu, M.: COVID-19 mobile positioning data contact tracing and patient privacy regulations: exploratory search of global response strategies and the use of digital tools in Nigeria. JMIR Mhealth Uhealth **8**(4), e19139 (2020)
60. Mehl, A., Bergey, F., Cawley, C., Gilsdorf, A.: Syndromic surveillance insights from a symptom assessment app before and during COVID-19 measures in Germany and the United Kingdom: results from repeated cross-sectional analyses. JMIR Mhealth Uhealth **8**(10), (2020)
61. Robbins, R., Affouf, M., Weaver, M.D., Czeisler, M.É., Barger, L.K., Quan, S.F., et al.: Estimated sleep duration before and during the COVID-19 pandemic in major metropolitan areas on different continents: observational study of smartphone app data. J. Med. Internet Res. **23**(2), e20546 (2021)

62. Rodriguez-Villa, E., Torous, J.: Regulating digital health technologies with transparency: the case for dynamic and multi-stakeholder evaluation. BMC Med. **17**(1), 226 (2019)
63. Becker, R., Thorogood, A., Ordish, J., Beauvais, M.J.S.: COVID-19 research: navigating the European general data protection regulation. J. Med. Internet Res. **22**(8), e19799 (2020)
64. Bradford, L., Aboy, M., Liddell, K.: COVID-19 contact tracing apps: a stress test for privacy, the GDPR, and data protection regimes. J. Law Biosci. **7**(1), lsaa034 (2020)
65. Shrestha, N., Shad, M.Y., Ulvi, O., Khan, M.H., Karamehic-Muratovic, A., Nguyen, U.D.T., et al.: The impact of COVID-19 on globalization. One Health **11**, 100180 (2020)

Synergistic Effects of Environmental Factors on the Spread of Corona Virus

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Abstract Epidemiology models, for studying the impact of different environmental factors on the dynamics of COVID-19 and its predictive mechanisms, gained considerable importance with the start of COVID-19 pandemic. This chapter is aimed majorly at determining the synergistic effect of different environmental factors on corona virus and its transmission dynamics. This kind of analysis is helpful for the health departments of the countries to take action according to the climate predictions and to improve the overall quality of care provided. These modeled predictions will also be helpful in alerting the people or applying lock downs during the weather conditions favorable for viral survival and dissemination. The study will lead to the answers: if there is worth worrying impact of the environmental factors on the corona virus, what is the measure of impact and lastly how and why they are possibly influencing the virus.

Keywords COVID-19 · Infectious disease · Environmental factors · Synergistic correlation · Modeling analysis

1 Introduction

Data driven insights are the major resources of health technologies and innovations which can improve healthcare systems and also help to resolve the complex health

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situations, like COVID-19. Data analytics can be helpful for health organizations to identify the level of major outbreaks as well as opportunities to provide better health-care monitoring system. Mathematical modeling is a fine way to provide valuable insights during an ongoing health emergency. It assists the health departments in creating solutions to enable a system delivering better care and applying improved intervention techniques.

Epidemiology models, for studying the impact of different environmental factors on the dynamics of COVID-19 as well as predictive mechanisms, gained considerable importance with the start of COVID-19 pandemic. The different types of models proved to be helpful for providing much needed information to the health legislators and policy makers during this emergency. This approach, in turn aid to reduce the infections and death rates significantly by taking the required precautionary measures [9, 28, 30, 41, 50, 55].

Among other models, discrete impact of different environmental factors including weather factors on the spread of corona virus has also been studied through different models [8, 29, 56, 72, 73, 76, 79, 80]. The determination of interaction between different environmental factors may provide interesting information regarding environmental influence on viral transmission. The unpublished data from our lab also revealed that the interaction of two or more environmental factors may affect the viral transmission positively or negatively.

Intense air pollution is one of the major global concerns in the present world. Smoke fog, commonly known as smog, and photo-chemical smog, commonly known as summer smog, are affecting the major cities in the world, adversely impacting the health of the individuals [4, 24, 66, 82]. During an outbreak of infectious diseases like COVID-19, which is actually targeting the respiratory system of the individuals, the additional effect of climatic conditions like particulate matter, NO_2, SO_2, CO_2 and O_3 could be highly dangerous for the people risking their lives even more. This scenario makes it vital to investigate whether the higher levels of pollution in winters and in summers have an impact on the COVID-19 infections and death rates.

This chapter covers synergistic effect of different climatic factors (humidity, dew point, precipitation, Air quality index (AQI) and temperature) on corona virus and its transmission dynamics in Pakistan. Based on the results obtained from statistical model, it was found that AQI has strong correlation with the COVID-19 spread. Therefore, in the later part of the chapter the pollutants (particulate matter, NO_2, SO_2, CO_2 and O_3) which contribute in AQI level were discussed and their mechanism in SARS-CoV2 dissemination was elaborated in detail. This kind of analysis is helpful for the health departments of the countries to take action according to the climate predictions. This analysis will also be helpful in alerting the people or applying lock downs during the peak periods under such weather conditions. The study will lead to the answers: if there is worth worrying impact of the studied factors on the corona virus, what is the measure of impact and lastly how and why they are possibly influencing the virus.

2 Environmental Factors and COVID-19

The current outbreak is the third time an animal coronavirus has infected humans in less than two decades. Like MERS CoV and SARS-CoV1, COVID-19 has been classified as a zoonotic coronavirus [42]. Its spread is not only limited to direct, indirect, or aerosol contact with affected people, but several environmental factors such as climate, temperature and air pollutants may have an impact on COVID-19 transmission, as has been observed with other viral respiratory infections [47]. With this learning, there came an urgent need of further investigation in this direction taking in account the environmental factors in order to minimize the risk of disease spread as well as forming the healthcare policies and managing the situation accordingly.

2.1 Weather Effects on COVID-19

Several researches have been conducted in various countries to study the impact of climatic conditions on SARS-CoV-2 transmission [2, 8, 17, 47, 48, 59, 65, 86]. Changes in temperature, for example, influence the stability of coronaviruses on surfaces and thus influence the transmission rate [79]. Similarly, a positive correlation between the transmission of COVID-19 and various meteorological factors such as dew point, relative and absolute humidity, temperature, and water vapor has been reported in a study conducted in Singapore [59]. Another study found that mean temperature was solely correlated to the spread of this deadly virus [86]. Absolute humidity was also found to have a strong association and had a key role in the dissemination of COVID-19 in South America [17]. On the basis of these research studies, it can be unanimously concluded that the environmental factors have an impact on the transmission of corona virus, however, there is still contradiction on whether the impact is positive or negative.

2.2 Synergies Between Weather Factors and COVID-19 Cases in Pakistan

Since the start of this pandemic, the scientists all around the globe are trying in their respective capacities to provide effective solutions for dealing with this health emergency. Predictive analytics and risk disease and management, as applications of healthcare analytics, are majorly used by the scientists during this pandemic. Various such research studies are conducted specifically to analyze the impact of environmental factors on the transmission of corona virus, COVID-19 cases and deaths. We conducted a novel case study in this regard, using a statistical model, considering the synergistic effect of different climatic conditions rather than their discrete effect on the COVID-19 transmission, which shows quite interesting results.

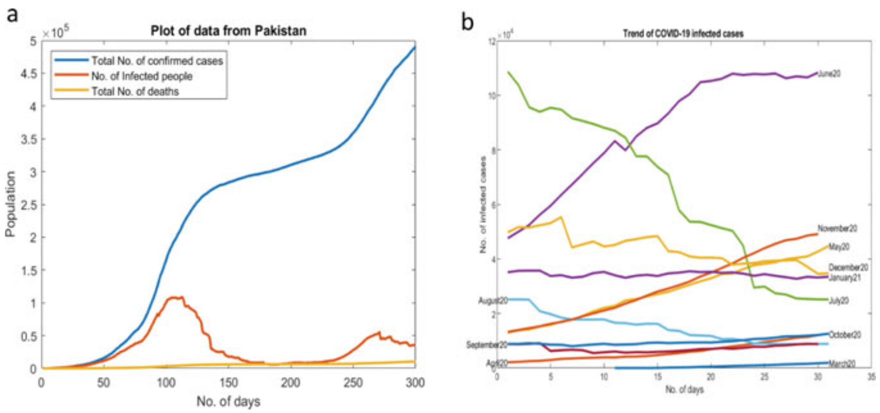

Fig. 1 **a** Plot of cumulative COVID-19 cases, daily cases and deaths in Pakistan. **b** Monthly trend of daily COVID-19 cases in Pakistan

In addition to the previous unpublished research study, a case study regarding the synergistic effects of different weather factors and Air Quality Index on the daily COVID-19 cases is conducted in Islamabad, the capital city of Pakistan. We examined and analyzed the data from 15th March to 31st July, 2020, collected from the official website of government of Pakistan (https://www.covid.gov.pk) using the regression model. The climatic factors considered in this study including temperature, dew point, humidity, precipitation and Air Quality Index (AQI), were assembled from Pakistan meteorological department (PMD) and official website: https://www.iqair.com/us/pakistan. The plot in Fig. 1a shows daily cases and deaths in Pakistan from March 2020 to January 2021. The cumulative number of confirmed cases, deaths and daily number of COVID-19 cases were plotted against the number of days. In order to identify clearly the pattern changes among the (summer and winter) months during COVID period, the daily COVID-19 infected cases were plotted. It can be clearly seen from the Fig. 1b that the month of June 2020 has witnessed the highest number of COVID-19 cases in Pakistan, while in the month of July 2020, the number of cases subsided rapidly. Besides other factors, the reason behind this phenomenon could possibly be the synergistic effect of temperature with the level of humidity and dew point present in the air, as analyzed in our unpublished data. Quasi Poisson regression model was used to analyze the aforementioned interactions. The daily infected cases of COVID-19 were taken as the dependent variable and the weather factors were taken as the independent variables. Air Quality Index was taken as the main factor and its interaction with other variables was investigated. The outcomes of the analysis were then plotted against the log predicted daily reported cases of COVID-19 obtained from the model (Fig. 2). It was observed from the outcome of the regression analysis that the impact of AQI interaction with humidity and with precipitation was higher in comparison with the other two variables that are temperature and dew point. It can be seen in Fig. 2a and 2d that the relation of AQI with the predicted cases changes from positive to negative for higher values of precipitation and humidity, respectively. A

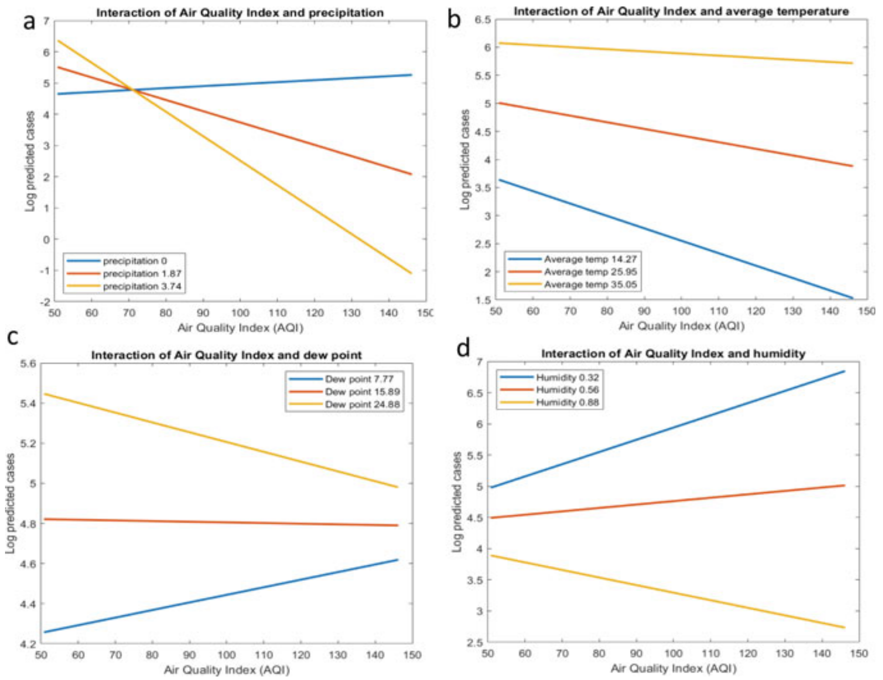

Fig. 2 Interaction of air quality index with **a** precipitation, **b** temperature, **c** dew point, and **d** humidity and their effect on daily COVID-19 cases

similar outcome can be seen in the case of the variable dew point (Fig. 2c), while temperature does not show any significant interaction with the AQI level (Fig. 2b). The results showed significant patterns and suggested that even though the AQI is getting higher, the higher values of humidity and precipitation have a positive impact on the daily number of cases. Although, the higher AQI level could aggravate the situation and adversely affect the transmission of the corona virus, higher humidity and precipitation levels can help us in these circumstances. On the contrary, the situation could be alarming at the places and time the humidity and precipitation levels are low and AQI level is high. This modeling analysis will help the health care providers to foresee the future patterns of disease prevalence and therefore can guide policy makers to devise strategies accordingly.

2.3 *Effect of Pollution on COVID-19*

Air pollution has been previously reported to aggravate the pathological outcomes of various respiratory viruses. A study, published after a century of Spanish influenza pandemic, reported that the cities with high coal combustion experienced tens of thousands of more flu deaths as compared to cities that used less coal [18]. Similarly, a study on SARS CoV-1 also revealed that people living in more polluted areas had two-fold higher risk of dying from SARS CoV-1 as compared to those living in less polluted areas [23]. A similar link is reported between COVID-19 pathology, mortality and air pollution exposure in humans (Table 1). Hence, it can be expected that the population already exposed to high air pollution is at increased risk of developing COVID-19 as compared to those experiencing good air quality [52]. The specific link between SARS CoV-2 infection and air pollution is still not completely understood but it might be speculated that compromised immune response, due to air pollution, facilitates viral penetration and replication. Moreover, the air pollution is also reported to be a major causative agent of cardiopulmonary disease, which might also contribute to exacerbate the COVID-19 pathogenesis [13]. Therefore, the possibility cannot be excluded that the virus would be facilitated in the cells whose integrity is already compromised by air pollution [21].

The air pollution is constituted from mixture of different gases and particulate matter. The particulate matter is comprised of an inner carbonaceous core which is coated by chemicals such as Sulphur, nitrate and metals. Additional biological pollutants such as bacteria and viruses may be adsorbed on the surface of particulate matter which amplify its toxicity [27]. Among gaseous pollutants the effect of NO_2, SO_2, CO and O_3 is most widely investigated on COVID-19 related pathology.

2.3.1 Particulate Matter

The particulate matter can increase the severity of COVID-19 disease expression in two ways. Firstly, the SARS CoV-2 has airborne transmission and presence of particulate matter act as a vehicle for viral transport to longer distances. Secondly, as the respiratory tract cells are first target of particulate matter, a long term exposure to these particulate matter compromises the health of these cell, which facilitates the entry of pathogens in the cells [21]. Up till now the epidemiological studies have investigated the effect of particulate matter with aerodynamic diameter 10 μm (PM_{10}) and 2.5 μm ($PM_{2.5}$) on COVID-19 pathogenesis. Both PM_{10} and $PM_{2.5}$ are ultrafine particles and their transportation and final destination within the blood stream and lungs is determined by the size of the particulate matter. The long and short term exposure to $PM_{2.5}$ is reported to be more strongly associated with COVID-19 infections and mortality than PM_{10} [3].

The $PM_{2.5}$ is mostly associated with negative impact on human health. Due to its small size it can easily penetrate into the lungs and cause serious respiratory issues [62]. These toxic particulate matter particles when inhaled lead to various serious health concerns which has led to development of a strong correlation between respiratory diseases, including SARS CoV-2, with particulate matter in various studies [37, 40, 51, 74]. It has been suggested that with an increase of only 1 $\mu g/m^3$ in $PM_{2.5}$ concentration, the COVID-19 cases escalate by 15% [81]. Thus exposure to $PM_{2.5}$ causes respiratory diseases and makes exposed population more prone to catching respiratory virus and developing severe symptoms [53].

Table 1 Epidemiological data on effect of air pollution on COVID-19

Location	Air pollutant exposure	Outcomes	Study duration	References
Italy	PM_{10} concentration exceeding daily limit value (50 μg/m^3)	Positive correlation between COVID-19 cases and PM_{10} daily limit value exceedance (R^2 = 0.98)	7th Feb–15th Mar 2020	[70]
Italy (12 cities)	Daily PM_{10} concentrations	No correlation was found between PM_{10} exposure and number of COVID-19 cases	10th Feb–27th Mar 2020	[12]
Italy (Milan)	Daily average concentration of NO_2 and O_3	Positive correlation of O_3 while negative correlation of NO_2 was observed with daily new positive COVID-19 cases and total deaths	1st Jan–30th Apr 2020	[88]
Italy (Milan)	Daily average concentration of PM_{10} and $PM_{2.5}$	Positive correlation was found between maximum PM_{10} concentration and daily new cases	1st Jan–30th Apr 2020	[89]
Italy	Mean $PM_{2.5}$ concentration in the month of February	Positive correlation of $PM_{2.5}$ with total number of cases and number of deaths	1st Feb–31st Mar 2020	[31]
Italy	AQI depending on values of PM_{10}, $PM_{2.5}$, NO_2, O_3 and SO_2	The COVID-19 related death rate was higher in Lombardy and Emilia Romagna, which are highly polluted by NO_2, as compared to rest of the Italy		[22]

(continued)

Table 1 (continued)

Location	Air pollutant exposure	Outcomes	Study duration	References
Italy	Daily data on distribution of $PM_{2.5}$, PM_{10}, O_3 and NO_2 and data for limit exceedance for at least 35 days during last decade	Significant positive correlation was observed between COVID-19 cases and exposure to atmospheric contaminants in 71 provinces of Italy	2010–2019	[26]
Italy (55 provinces)	PM_{10} concentration	High association between COVID-19 and air pollution in Northern Italy	From start of COVID-19 till 7th Apr 2020	[19]
China (Wuhan, Huanggang and Xiao Gan)	Daily data of air pollutants (PM_{10}, $PM_{2.5}$, CO, SO_2, NO_2 and 8-h O_3) and meteorological variables (temperature, relative humidity and wind)	$PM_{2.5}$ and relative humidity are substantially associated with elevated risk of COVID-19 while PM_{10} and temperature are associated with decreased COVID-19 risk	10th Feb–10th Apr 2020	[38]
China (63 cities)	Hourly NO_2 data	Positive association between NO_2 concentration and number of daily confirmed cases in all the cities	27th Jan–26th Feb 2020	[83]
China (72 cities)	Daily $PM_{2.5}$ and PM_{10} concentration	Positive association between COVID-19 cases and each 10 $\mu g/m^3$ increase in concentration of $PM_{2.5}$ and PM_{10}	20th Jun–2nd Mar 2020	[78]
China (120 cities)	Daily air pollutant concentration (PM_{10}, $PM_{2.5}$, NO_2, CO, SO_2 and O_3)	A 10 $\mu g/m^3$ increase (lag0 to lag 14) in PM_{10}, $PM_{2.5}$, O_3 and NO_2 was associated with increase in daily conformed cases whereas similar increase in SO_2 was associated with a decrease in confirmed COVID-19 cases	23rd Jan to 29th Feb 2020	[87]

(continued)

Table 1 (continued)

Location	Air pollutant exposure	Outcomes	Study duration	References
Europe (107 major Italian cities and 47 European capitals)	Hourly concentrations of PM_{10}, $PM_{2.5}$, NH_3 and O_3	Positive correlation between daily confirmed cases/million and PM_{10}, $PM_{2.5}$ and NH_3. However O_3 showed negative correlation	10 Feb–10 Apr 200	[32]
Europe (66 administrative regions in Italy, France, Germany and Spain)	Tropospheric NO_2 concentration taking vertical air flow into account	Sentinel-5P data revealed two most polluted hotspots in Europe i.e. Northern Italy and Madrid metropolitan area where COVID-19 mortality is very high	Jan–Feb 2020	[58]
The Netherlands (355 municipilaties)	$PM_{2.5}$, NO_2 or SO_2 average annual concentration from 2015 to 2019	A 1 $\mu g/m^3$ rise in $PM_{2.5}$ level is associated with 9.4 more COVID19 confirmed cases, 3 more hospitalizations and 2.3 more COVID-19 associated mortalities	From start of COVID-19 to 5 June 2020	[20]
Peru (24 districts of Lima)	$PM_{2.5}$ concentration	Previous increased exposure to $PM_{2.5}$ in metropolitan Lima is attributable for higher COVID-19 rates	From start of COVID-19 to 12th Jun 2020	[77]
USA (Queens NY)	Daily average $PM_{2.5}$ and maximum 8 h O_3	A positive association of confirmed cases was observed with O_3 but a negative correlation was observed for $PM_{2.5}$	1st Mar–20th Apr 2020	[1]
USA (all inland counties)	Long term $PM_{2.5}$ average between 2000 and 2016	A 1 $\mu g/m^3$ increase in $PM_{2.5}$ level causes an 8% increase in COVID-19 associated death rate	From start of COVID-19 to 4th Apr 2020	[81]

(continued)

Table 1 (continued)

Location	Air pollutant exposure	Outcomes	Study duration	References
USA (3122 counties)	County-level long term exposure to $PM_{2.5}$, O_3 and NO_2 from 2010 to 2016	A 4.6 ppb increase in NO_2 concentration is associated with a 7.1% increase in COVID-19 fatality rate and 11.2% mortality rate. The association with $PM_{2.5}$ and O_3 was insignificant	22nd Jan–29th Apr 2020	[45]
Worldwide	From start of COVID-19 to Jun 2020	Chronic $PM_{2.5}$ exposure in 2019 prior to COVID-19 outbreak	$PM_{2.5}$ contributes 15% increase in COVID-19 mortality worldwide, 27% increase in East Asia, 19% increase in Europe and increase in 17% in North America	[64]

The particulate matter also contains metals which have cytotoxic effects on the cells. When the particulate matter reaches the target tissue, a direct interaction between the particle and cells elicit an immune response resulting in systemic inflammation and sustained oxidative stress [10]. The particulate matter exposure can affect the lungs via following mechanisms.

1. ***Compromised immune response***

The particulate matter affects immune response in different ways. The macrophages play a fundamental role in immune system by phagocytizing the foreign particle. This phagocytic capability is also reported to be compromised after pollution exposure and therefore the macrophages will be unable to inactivate the virus [39].

When the particulate matter enters the body, these are taken as foreign bodies and immune system is activated against these foreign particles. In this situation, if the respiratory virus enters the body, the immune response, being active against both the virus and the particulate matter, is less effective as compared to the immune response focused on defense against respiratory virus only [10].

2. ***Inflammation***

Inflammation is a response of our immune system which is indispensable. The particulate matter has the ability to induce strong inflammatory response as a result of which high levels of pro inflammatory cytokines, TNF-α and IL-6 were observed in blood of mice exposed to PM_{10} and $PM_{2.5}$ samples [49]. Similarly, an analysis of lung cells has also shown elevated levels of IL-8 in humans exposed to pollutants [84]. As it is already known that the cytokine storm is the major culprit in COVID-19-induced damage, therefore, the predisposition of individuals, exposed to particulate matter over a long time, towards an amplified cytokine storm, following SARS CoV2 infection, may be assumed. This may also explain the correlation between COVID-19 and particulate matter that has been associated with high mortality in polluted areas [21].

3. ***Oxidative stress***

The pollutant particles are reported to increase reactive oxygen species which are indicative of oxidative stress [11].

4. ***Interaction with ACE2 receptor***

The angiotensin converting enzyme-2 (ACE2) receptors are expressed in heart, arteries, kidneys, lungs and intestine, due to their important role in blood pressure regulation via cleavage of angiotensin 2. The angiotensin 2 binds to AT1 receptor and causes vasoconstriction and inflammation [16]. The ACE2 receptor cleaves angiotensin 2 into angiotensin 1–7 which are vasodilator and anti-inflammatory [35]. In severe forms of COVID-19, it has been reported that an imbalance is created in ACE2/AT1 receptors [16, 67]. Similarly, exposure to particulate matter causes an increase in the expression of AT1 receptor. Therefore, combined effect, of PM induced elevated expression of AT1 receptor and SARS CoV-2 induced ACE2/AT1 receptor imbalance, may heighten the inflammatory response, as observed in severe cases of COVID-19 [13]. Moreover, PM also increases the expression of ACE receptor (that converts angiotensin 1–7 to angiotensin 2) and therefore, leads to an increase in the AT1 receptor-angiotensin 2 liaison [5]. The ACE2 receptor also protects against inflammation, via inhibition of NFκB (inflammatory response activation pathway) and activation of NRF2 (pathway that activates anti-inflammatory pathway). The COVID-19 binding to ACE2 receptor blocks its activity, and thus alters this mechanism which leads to destructive hyper-inflammatory response [21].

The ACE2 receptors are also a source of corona virus entry into the cell. The virus binds to the ACE2 receptors with the help of its receptor binding domain and is later activated by human cellular proteases [71]. Due to the importance of proteases, it has been reported that inhibiting these proteases might be a potent option to block viral entry [36]. The particulate matter causes activation of these proteases and therefore, facilitate viral entry [85]. The exposure to $PM_{2.5}$ is also reported to cause overexpression of ACE2 receptor, and this receptor being the entry key for virus into the cell, the elevated COVID-19 infection is also plausible [46].

2.3.2 Nitrogen Dioxide (NO_2)

In the urban environment NO_2 is a major air pollutant arising from traffic and industrial smoke. The NO_2 has been reported to be associated with various respiratory disorders including asthma, bronchiolitis, chronic obstructive pulmonary disease (COPD) and cardiovascular disease [7]. The association of NO_2 with the COVID-19 is established in many studies. In a study from England it has been reported that high death rate in London and midland may be because of highest average concentration of NO_2 annually [75]. The nitrogen oxide induced systemic oxidative stress resulting in decreased pulmonary function [34] may also contribute to increased infectivity of respiratory viruses including COVID-19. Another study revealed that prolonged exposure to the high levels of NO_2 causes extreme illness such as diabetes, cardiovascular disease, hypertension and even death in some cases [43]. Long term inhalation in air concentrated with NO_2 causes cytokine Inflammation in the lungs which lead to chronic respiratory disorders [63]. A study was held in eight countries to examine the effect of air pollutants on the infectivity and mortality rate of COVID-19. The study revealed that all countries which include UK, France, USA, China, Italy, Iran, Spain and Germany showed higher percentage of viral infections in the regions having high levels of NO_2 in the air [60]. Another retrospective study was done in Wuhan and Xioa Gan in China which revealed a strong correlation between NO_2 and number of COVID-19 cases [44]. A significant association was found between COVID-19 and NO_2 in 12 cities of China. It has been estimated that every 10 $\mu g/m^3$ increase in NO_2 levels in air caused 6.94% increase in daily COVID-19 cases [87]. Other studies held in India also showed a positive correlation between NO_2 and COVID-19 infectivity [14]. A study held in France demonstrated that nitrogen dioxide and nitrous oxide called as NOx is contributing towards the formation of secondary particles by the process of transformation in the presence of photochemical reactions with nitric acid and ozone. These are the major contributing factors towards acid rain as well [57]. Although a lot of studies has been done on the relationship between NO_2

and COVID-19, but there is a debate among the scientists that other factors, such as population density, should be incorporated in the studies in order to understand the impact of air pollution on COVID-19 in real terms. In this regard, an empirical study was held in France to check the relationship between NO_2 and COVID-19 associated mortality rate. They used artificial neural network experiments to reveal the threshold value of NO_2 that is adept of inducing adverse effect related to COVID-19 deaths. They calculated the threshold values as 21.8 $\mu g/m^3$, 22.9 $\mu g/m^3$ and 15.8 $\mu g/m^3$ for three French cities Lyon, Paris and Marseille, respectively, by considering population density in the model as well [54]. More such studies are needed to identify the potential threshold values for different geographical populations of diverse densities to mimic the factors contributing to the spread of new pandemics.

2.3.3 Carbon Dioxide (CO_2)

Other air pollutants that can stimulate the rate of spread of new pandemics and mortality rate are CO_2, O_3 and Sox. The major contributors of these pollutants are Green House Gases (GHGs) that are directly release into the environment by the combustion of fuels [15]. Air is termed as polluted air when it contains elevated level of primary pollutants such as Methane, Cox, Sox and NOx and secondary pollutants as well which include Sulphur trioxide and Ozone [6].

According to one study held in the University of Colorado Boulder and the Cooperative Institute for Research in Environmental Sciences (CIRES), when the level of indoor CO_2 has been doubled, it increases the risk of spread of infection by two folds. According to them when an infectious person exhales CO_2, it is accompanied with the air borne viruses as well. In this way CO_2 can serve as the proxy in the spread of infections [61]. They suggested that monitoring the level of CO_2 indoors can be helpful in determining the rate of infection spread in the closed environments such as Buses, Library, classrooms and gyms. They tested that during the COVID-19 pandemic the rate of spread of infections in indoor shared air has been dependent on the activities of the individuals, such as a person sitting quietly in the library will exhale less CO_2 as compared to the person doing gym. In this manner, the level of CO_2 monitoring can be served as a low cost and robust method for the determination of virus count in closed air [61]. Moreover, another study revealed the mechanism of corona virus spread with CO_2. According to them the density of CO_2 (1.96 g/L) is quite higher than the density of the air (1.28 g/L). The higher the level of CO_2 in air, the higher is the density of the air which promotes the spread of Corona virus in the air. Viral droplets start moving and floating in the high density air and can travel up to certain distance of high altitudes and can stay there for longer periods. In this way the concentration of CO_2 serves as the driving factor for COVID-19 spread in the air. According to their assumptions Corona virus needs CO_2 for its survival and reproduction and it always moves from low concentrations of CO_2 towards higher concentration regions of CO_2. The concentration of CO_2 in air is 100 times lower (0.04% by volume) as compared to the human lungs (4–5%) which favors the virus to move from air to human lungs through respiratory path and reaches human lung where it causes inflammation and in acute cases it causes death in humans. Once it reaches the human lungs, it starts the replication and the viral particles come out with cough and are ready to infect other persons who are already immune-compromised and are exhaling more CO_2 as compared to the normal individuals. The virus attacks them and this cycle of infectivity continues [33]. Hence, it has been concluded that CO_2 does play a vital role in the spread of COVID-19, but more studies are needed to determine the threshold level of CO_2 to mimic the spread of COVID-19.

2.3.4 Ozone (O_3)

The elevated levels of ozone at lower altitude adversely impact the humans by producing free radicals which badly affect the lung functions, respiratory tract and asthma. This leads to increase the chances of hospitalization and rate of mortality [68]. Furthermore, it has been studied that individual living at high altitudes such as Tibet and Bolivia were less susceptible to the COVID-19, because, virus half-life was being compromised at high altitudes or due to the hypoxia down regulation of ACE2 in COVID-19 pulmonary epithelium. Moreover, they further stated that at high altitudes the UVA and UVB radiations are more intense and they act as natural sanitizers against COVID-19 [69]. But in literature different studies revealed that O_3 has the potential to work against the COVID-19 infection by its potential of oxidation, peroxidation and generation of free radicals that cause lipid membrane permeability in viruses. Moreover, O_3 concentration adversely affects the virus capsid and disturbs its reproductive cycle by hindering the cell to cell interaction through peroxidation [25].

3 Conclusion

This study concluded that environmental factors definitely have some impact on the rate of spread and level of infectivity in pandemics such as COVID-19. However, the impact of weather factors and pollutions are not conclusive alone, if demography, population density, existence of co-morbidities and epidemiology have not been taken into consideration. These factors may play a vital role in determining the dynamics of pandemic spread through mathematical and statistical models, globally. Hence, data (population density, epidemiology, pollution level) from each continent and region of the world must be collected on regular basis. This investment in data and mathematical model developed will be a valuable asset for the healthcare leaders which allow them to foresee the meaningful patterns of the pandemics. This will ultimately provide healthcare systems a better direction to proceed for making improved surveillance system to cope with pandemics. This requires the input from policy makers and think tanks of the countries to make regional reforms and policies to update the data, which will be helpful to control the new pandemics in future.

References

1. Adhikari, A., Yin, J.: Short-term effects of ambient ozone, PM2.5, and meteorological factors on COVID-19 confirmed cases and deaths in Queens, New York. Int. J. Environ. Res. Public Health **17**, 4047 (2020)
2. Ahmadi, M., Sharifi, A., Dorosti, S., Ghoushchi, S.J., Ghanbari, N.: Investigation of effective climatology parameters on COVID-19 outbreak in Iran. Sci. Total Environ. **729**, 138705 (2020)
3. Ali, N., Islam, F.: The effects of air pollution on COVID-19 infection and mortality—a review on recent evidence. Front. Public Health **8**, (2020)
4. Ali, Y., Razi, M., De Felice, F., Sabir, M., Petrillo, A.: A VIKOR based approach for assessing the social, environmental and economic effects of "smog" on human health. Sci. Total Environ. **650**, 2897–2905 (2019)
5. Alifano, M., Alifano, P., Forgez, P., Iannelli, A.: Renin-angiotensin system at the heart of COVID-19 pandemic. Biochimie **174**, 30–33 (2020)
6. Anjum, N.A.: Good in the worst: COVID-19 restrictions and ease in global air pollution (2020)
7. Atkinson, R.W., Butland, B.K., Anderson, H.R., Maynard, R.L.: Long-term concentrations of nitrogen dioxide and mortality: a meta-analysis of cohort studies. Epidemiol. (Camb., Mass.) **29**, 460 (2018)
8. Bashir, M.F., Ma, B., Komal, B., Bashir, M.A., Tan, D., Bashir, M.: Correlation between climate indicators and COVID-19 pandemic in New York, USA. Sci. Total Environ. **728**, 138835 (2020)
9. Bastos, S.B., Cajueiro, D.O.: Modeling and forecasting the early evolution of the Covid-19 pandemic in Brazil. Sci. Rep. **10**, 1–10 (2020)
10. Becker, S., Soukup, J.M.: Exposure to urban air particulates alters the macrophage-mediated inflammatory response to respiratory viral infection. J. Toxicol. Environ. Health Part A **57**, 445–457 (1999)
11. Bengalli, R., Zerboni, A., Marchetti, S., Longhin, E., Priola, M., Camatini, M., Mantecca, P.: In vitro pulmonary and vascular effects induced by different diesel exhaust particles. Toxicol. Lett. **306**, 13–24 (2019)
12. Bontempi, E.: First data analysis about possible COVID-19 virus airborne diffusion due to air particulate matter (PM): the case of Lombardy (Italy). Environ. Res. **186**, 109639 (2020)
13. Bourdrel, T., Annesi-Maesano, I., Alahmad, B., Maesano, C.N., Bind, M.-A.: The impact of outdoor air pollution on COVID-19: a review of evidence from in vitro, animal, and human studies. Eur. Respir. Rev. **30**, (2021)
14. Chakraborty, P., Jayachandran, S., Padalkar, P., Sitlhou, L., Chakraborty, S., Kar, R., Bhaumik, S., Srivastava, M.: Exposure to nitrogen dioxide (NO_2) from vehicular emission could increase the COVID-19 pandemic fatality in India: a perspective. Bull. Environ. Contam. Toxicol. **105**, 198–204 (2020)
15. Change, C.: Climate change impacts, adaptation and vulnerability. Sci. Total Environ. **326**, 95–112 (2007)
16. Cheng, H., Wang, Y., Wang, G.Q.: Organ-protective effect of angiotensin-converting enzyme 2 and its effect on the prognosis of COVID-19. J. Med. Virol. **92**, 726–730 (2020)
17. Chien, L.-C., Chen, L.-W.: Meteorological impacts on the incidence of COVID-19 in the US Stoch. Environ. Res. Risk Assess. **34**, 1675–1680 (2020)
18. Clay, K., Lewis, J., Severnini, E.: Pollution, infectious disease, and mortality: evidence from the 1918 Spanish influenza pandemic. J. Econ. Hist. **78**, 1179–1209 (2018)
19. Coccia, M.: Factors determining the diffusion of COVID-19 and suggested strategy to prevent future accelerated viral infectivity similar to COVID. Sci. Total Environ. **729**, 138474 (2020)
20. Cole, M., Ozgen, C., Strobl, E.: Air pollution exposure and Covid-19. IZA Discussion Papers No. 13367, Institute of Labor Economics, Bonn
21. Comunian, S., Dongo, D., Milani, C., Palestini, P.: Air pollution and Covid-19: the role of particulate matter in the spread and increase of Covid-19's morbidity and mortality. Int. J. Environ. Res. Public Health **17**, 4487 (2020)

22. Conticini, E., Frediani, B., Caro, D.: Can atmospheric pollution be considered a co-factor in extremely high level of SARS-CoV-2 lethality in Northern Italy? Environ. Pollut. **261**, 114465 (2020)
23. Cui, Y., Zhang, Z.-F., Froines, J., Zhao, J., Wang, H., Yu, S.-Z., Detels, R.: Air pollution and case fatality of SARS in the People's Republic of China: an ecologic study. Environ. Health **2**, 1–5 (2003)
24. David, H., Juyuan, J.: A study of smog issues and PM 2.5 pollutant control strategies in China. J. Environ. Prot. **4**, 746–752 (2013)
25. Elvis, A., Ekta, J.: Ozone therapy: a clinical review. J. Nat. Sci., Biol., Med. **2**, 66 (2011)
26. Fattorini, D., Regoli, F.: Role of the chronic air pollution levels in the Covid-19 outbreak risk in Italy. Environ. Pollut. **264**, 114732 (2020)
27. Feng, S., Gao, D., Liao, F., Zhou, F., Wang, X.: The health effects of ambient PM2. 5 and potential mechanisms. Ecotoxicol. Environ. Saf. **128**, 67–74 (2016)
28. Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunuba Perez, Z., Cuomo-Dannenburg, G.: Report 9: impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand (2020)
29. Ficetola, G.F., Rubolini, D.: Climate affects global patterns of COVID-19 early outbreak dynamics. MedRxiv (2020)
30. Fredj, H.B., Chérif, F.: Novel corona virus disease infection in Tunisia: mathematical model and the impact of the quarantine strategy. Chaos, Solitons Fractals **138**, 109969 (2020)
31. Frontera, A., Cianfanelli, L., Vlachos, K., Landoni, G., Cremona, G.: Severe air pollution links to higher mortality in COVID-19 patients: the "double-hit" hypothesis. J. Infect. **81**, 255–259 (2020)
32. Fronza, R., Lusic, M., Schmidt, M., Lucic, B.: Spatial–temporal variations in atmospheric factors contribute to SARS-CoV-2 outbreak. Viruses **12**, 588 (2020)
33. Garai, A.: Effect of atmospheric carbon dioxide on coronavirus. Indian J. Environ. Sci. **16**, 114 (2020)
34. Guarnieri, M., Balmes, J.R.: Outdoor air pollution and asthma. Lancet **383**, 1581–1592 (2014)
35. Hayashi, N., Yamamoto, K., Ohishi, M., Tatara, Y., Takeya, Y., Shiota, A., Oguro, R., Iwamoto, Y., Takeda, M., Rakugi, H.: The counterregulating role of ACE2 and ACE2-mediated angiotensin 1–7 signaling against angiotensin II stimulation in vascular cells. Hypertens. Res. **33**, 1182–1185 (2010)
36. Hoffmann, M., Kleine-Weber, H., Schroeder, S., Krüger, N., Herrler, T., Erichsen, S., Schiergens, T.S., Herrler, G., Wu, N.-H., Nitsche, A.: SARS-CoV-2 cell entry depends on ACE2 and TMPRSS2 and is blocked by a clinically proven protease inhibitor. Cell **181**, 271–280.e8 (2020)
37. Horne, B.D., Joy, E.A., Hofmann, M.G., Gesteland, P.H., Cannon, J.B., Lefler, J.S., Blagev, D.P., Korgenski, E.K., Torosyan, N., Hansen, G.I.: Short-term elevation of fine particulate matter air pollution and acute lower respiratory infection. Am. J. Respir. Crit. Care Med. **198**, 759–766 (2018)
38. Jiang, Y., Wu, X.-J., Guan, Y.-J.: Effect of ambient air pollutants and meteorological variables on COVID-19 incidence. Infect. Control Hosp. Epidemiol. **41**, 1011–1015 (2020)
39. Kaan, P.M., Hegele, R.G.: Interaction between respiratory syncytial virus and particulate matter in guinea pig alveolar macrophages. Am. J. Respir. Cell Mol. Biol. **28**, 697–704 (2003)
40. Kelly, F., Fussell, J.: Air pollution and airway disease. Clin. Exp. Allergy **41**, 1059–1071 (2011)
41. Kennedy, D.M., Zambrano, G.J., Wang, Y., Neto, O.P.: Modeling the effects of intervention strategies on COVID-19 transmission dynamics. J. Clin. Virol. **128**, 104440 (2020)
42. Kumar, D., Malviya, R., Sharma, P.K.: Corona virus: a review of COVID-19. EJMO **4**, 8–25 (2020)
43. Lelieveld, J., Evans, J.S., Fnais, M., Giannadaki, D., Pozzer, A.: The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature **525**, 367–371 (2015)
44. Li, H., Xu, X.-L., Dai, D.-W., Huang, Z.-Y., Ma, Z., Guan, Y.-J.: Air pollution and temperature are associated with increased COVID-19 incidence: a time series study. Int. J. Infect. Dis. **97**, 278–282 (2020)

45. Liang, D., Shi, L., Zhao, J., Liu, P., Sarnat, J.A., Gao, S., Schwartz, J., Liu, Y., Ebelt, S.T., Scovronick, N.: Urban air pollution may enhance COVID-19 case-fatality and mortality rates in the United States. Innovation **1**, 100047 (2020)
46. Lin, C.-I., Tsai, C.-H., Sun, Y.-L., Hsieh, W.-Y., Lin, Y.-C., Chen, C.-Y., Lin, C.-S.: Instillation of particulate matter 2.5 induced acute lung injury and attenuated the injury recovery in ACE2 knockout mice. Int. J. Biol. Sci. **14**, 253 (2018)
47. Liu, J., Zhou, J., Yao, J., Zhang, X., Li, L., Xu, X., He, X., Wang, B., Fu, S., Niu, T.: Impact of meteorological factors on the COVID-19 transmission: a multi-city study in China. Sci. Total Environ. **726**, 138513 (2020)
48. Ma, Y., Zhao, Y., Liu, J., He, X., Wang, B., Fu, S., Yan, J., Niu, J., Zhou, J., Luo, B.: Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. Sci. Total Environ. **724**, 138226 (2020)
49. Mantecca, P., Gualtieri, M., Longhin, E., Bestetti, G., Palestini, P., Bolzacchini, E., Camatini, M.: Adverse biological effects of Milan urban PM looking for suitable molecular markers of exposure. Chem. Ind. Chem. Eng. Q. **18**, 635–641 (2012)
50. Meehan, M.T., Rojas, D.P., Adekunle, A.I., Adegboye, O.A., Caldwell, J.M., Turek, E., Williams, B.M., Marais, B.J., Trauer, J.M., McBryde, E.S.: Modelling insights into the COVID-19 pandemic. Paediatr. Respir. Rev. **35**, 64–69 (2020)
51. Mehmood, K., Ahmad, H.R., Abid, A.A., Guo, P.: A preliminary assessment and control strategy of size segregated pollutants in urban and peri-urban areas of Metropolitan Faisalabad, Pakistan. Pak. J. Anal. Environ. Chem. **19**, 146–152 (2018)
52. Mehmood, K., Bao, Y., Petropoulos, G.P., Abbas, R., Abrar, M.M., Mustafa, A., Soban, A., Saud, S., Ahmad, M., Hussain, I.: Investigating connections between COVID-19 pandemic, air pollution and community interventions for Pakistan employing geoinformation technologies. Chemosphere **272**, 129809 (2021)
53. Mehmood, K., Saifullah, M.I., Abrar, M.M.: Can exposure to PM2. 5 particles increase the incidence of coronavirus disease 2019 (COVID-19)? Sci. Total Environ. (2020)
54. Mele, M., Magazzino, C., Schneider, N., Strezov, V., NO_2 levels as a contributing factor to COVID-19 deaths: the first empirical estimate of threshold values. Environ. Res. **194**, 110663 (2021)
55. Ndaïrou, F., Area, I., Nieto, J.J., Torres, D.F.: Mathematical modeling of COVID-19 transmission dynamics with a case study of Wuhan. Chaos, Solitons Fractals **135**, 109846 (2020)
56. Neher, R.A., Dyrdak, R., Druelle, V., Hodcroft, E.B., Albert, J.: Potential impact of seasonal forcing on a SARS-CoV-2 pandemic. Swiss Med. Wkly. **150**, (2020)
57. Nguyen, H.T., Kim, K.-H., Park, C.: Long-term trend of NO_2 in major urban areas of Korea and possible consequences for health. Atmos. Environ. **106**, 347–357 (2015)
58. Ogen, Y.: Assessing nitrogen dioxide (NO_2) levels as a contributing factor to coronavirus (COVID-19) fatality. Sci. Total Environ. **726**, 138605 (2020)
59. Pani, S.K., Lin, N.-H., RavindraBabu, S.: Association of COVID-19 pandemic with meteorological parameters over Singapore. Sci. Total Environ. **740**, 140112 (2020)
60. Pansini, R., Fornacca, D.: Higher virulence of COVID-19 in the air-polluted regions of eight severely affected countries. medRxiv (2020)
61. Peng, Z., Jimenez, J.L.: Exhaled CO_2 as a COVID-19 infection risk proxy for different indoor environments and activities. Environ. Sci. Technol. Lett. **8**, 392–397 (2021)
62. Perrone, M., Gualtieri, M., Consonni, V., Ferrero, L., Sangiorgi, G., Longhin, E., Ballabio, D., Bolzacchini, E., Camatini, M.: Particle size, chemical composition, seasons of the year and urban, rural or remote site origins as determinants of biological effects of particulate matter on pulmonary cells. Environ Pollut. **176**, 215–227 (2013)
63. Petit, P.C., Fine, D.H., Vásquez, G.B., Gamero, L., Slaughter, M.S., Dasse, K.A.: The pathophysiology of nitrogen dioxide during inhaled nitric oxide therapy. ASAIO J. **63**, 7–13 (2017)
64. Pozzer, A., Dominici, F., Haines, A., Witt, C., Münzel, T., Lelieveld, J.: Regional and global contributions of air pollution to risk of death from COVID-19. Cardiovasc. Res. **116**, 2247–2253 (2020)

65. Prata, D.N., Rodrigues, W., Bermejo, P.H.: Temperature significantly changes COVID-19 transmission in (sub) tropical cities of Brazil. Sci. Total Environ. **729**, 138862 (2020)
66. Rani, B., Singh, U., Chuhan, A., Sharma, D., Maheshwari, R.: Photochemical smog pollution and its mitigation measures. J. Adv. Sci. Res. **2**, (2011)
67. Rivellese, F., Prediletto, E.: ACE2 at the centre of COVID-19 from paucisymptomatic infections to severe pneumonia. Autoimmun. Rev. **19**, 102536 (2020)
68. Semple, J.L., Moore, G.K., Koutrakis, P., Wolfson, J.M., Cristofanelli, P., Bonasoni, P.: High concentrations of ozone air pollution on Mount Everest: health implications for Sherpa communities and mountaineers. High Alt. Med. Biol. **17**, 365–369 (2016)
69. Semple, J., Moore, G.: High levels of ambient ozone (O_3) may impact COVID-19 in high altitude mountain environments. Respir. Physiol. Neurobiol. **280**, 103487 (2020)
70. Setti, L., Passarini, F., De Gennaro, G., Barbieri, P., Perrone, M.G., Piazzalunga, A., Borelli, M., Palmisani, J., Di Gilio, A., Piscitelli, P.: The potential role of particulate matter in the spreading of COVID-19 in northern Italy: first evidence-based research hypotheses. MedRxiv (2020)
71. Shang, J., Wan, Y., Luo, C., Ye, G., Geng, Q., Auerbach, A., Li, F.: Cell entry mechanisms of SARS-CoV-2. Proc. Natl. Acad. Sci. **117**, 11727–11734 (2020)
72. Shi, P., Dong, Y., Yan, H., Zhao, C., Li, X., Liu, W., He, M., Tang, S., Xi, S.: Impact of temperature on the dynamics of the COVID-19 outbreak in China. Sci. Total Environ. **728**, 138890 (2020)
73. Sobral, M.F.F., Duarte, G.B., da Penha Sobral, A.I.G., Marinho, M.L.M., de Souza Melo, A.: Association between climate variables and global transmission oF SARS-CoV-2. Sci. Total Environ. **729**, 138997 (2020)
74. Su, W., Wu, X., Geng, X., Zhao, X., Liu, Q., Liu, T.: The short-term effects of air pollutants on influenza-like illness in Jinan, China. BMC Public Health **19**, 1–12 (2019)
75. Travaglio, M., Yu, Y., Popovic, R., Selley, L., Leal, N.S., Martins, L.M.: Links between air pollution and COVID-19 in England. Environ. Pollut. **268**, 115859 (2021)
76. Ujiie, M., Tsuzuki, S., Ohmagari, N.: Effect of temperature on the infectivity of COVID-19. Int. J. Infect. Dis. **95**, 301–303 (2020)
77. Vasquez-Apestegui, B.V., Parras-Garrido, E., Tapia, V., Paz-Aparicio, V.M., Rojas, J.P., Sanchez-Ccoyllo, O.R., Gonzales, G.F.: Association between air pollution in Lima and the high incidence of COVID-19: findings from a post hoc analysis. BMC Public Health **21**, 1–13 (2021)
78. Wang, B., Liu, J., Fu, S., Xu, X., Li, L., Ma, Y., Zhou, J., Yao, J., Liu, X., Zhang, X.: An effect assessment of airborne particulate matter pollution on COVID-19: a multi-city study in China. MedRxiv (2020)
79. Wang, J., Tang, K., Feng, K., Li, X., Lv, W., Chen, K., Wang, F.: High temperature and high humidity reduce the transmission of COVID-19 (2020). arXiv preprint arXiv:2003.05003
80. Wu, Y., Jing, W., Liu, J., Ma, Q., Yuan, J., Wang, Y., Du, M., Liu, M.: Effects of temperature and humidity on the daily new cases and new deaths of COVID-19 in 166 countries. Sci. Total Environ. **729**, 139051 (2020)
81. Wu, X., Nethery, R.C., Sabath, B.M., Braun, D., Dominici, F.: Exposure to air pollution and COVID-19 mortality in the United States. MedRxiv (2020)
82. Yang, L.E., Hoffmann, P., Scheffran, J.: Health impacts of smog pollution: the human dimensions of exposure. Lancet Planet. Health **1**, e132–e133 (2017)
83. Yao, Y., Pan, J., Liu, Z., Meng, X., Wang, W., Kan, H., Wang, W.: Ambient nitrogen dioxide pollution and spreadability of COVID-19 in Chinese cities. Ecotoxicol. Environ. Saf. **208**, 111421 (2021)
84. Zerboni, A., Bengalli, R., Baeri, G., Fiandra, L., Catelani, T., Mantecca, P.: Mixture effects of diesel exhaust and metal oxide nanoparticles in human lung A549 cells. Nanomaterials **9**, 1302 (2019)
85. Zheng, Y.-Y., Ma, Y.-T., Zhang, J.-Y., Xie, X.: COVID-19 and the cardiovascular system. Nat. Rev. Cardiol. **17**, 259–260 (2020)

86. Zhu, L., Liu, X., Huang, H., Avellán-Llaguno, R.D., Lazo, M.M.L., Gaggero, A., Soto-Rifo, R., Patiño, L., Valencia-Avellan, M., Diringer, B.: Meteorological impact on the COVID-19 pandemic: a study across eight severely affected regions in South America. Sci. Total Environ. **744**, 140881 (2020)
87. Zhu, Y., Xie, J., Huang, F., Cao, L.: Association between short-term exposure to air pollution and COVID-19 infection: evidence from China. Sci. Total Environ. **727**, 138704 (2020)
88. Zoran, M.A., Savastru, R.S., Savastru, D.M., Tautan, M.N.: Assessing the relationship between ground levels of ozone (O_3) and nitrogen dioxide (NO_2) with coronavirus (COVID-19) in Milan, Italy. Sci. Total Environ. **740**, 140005 (2020)
89. Zoran, M.A., Savastru, R.S., Savastru, D.M., Tautan, M.N.: Assessing the relationship between surface levels of PM2. 5 and PM10 particulate matter impact on COVID-19 in Milan, Italy. Sci. Total Environ. **738**, 139825 (2020)

CFD Analysis of COVID-19 Dispersion via Speaking, Breathing, Coughing, and (or) Sneezing

Mohammad Taeibi Rahni and Seyedehkoukab Gouharianmohammadi

Abstract All human respiratory exhalations (breathing, laughing, singing, talking, coughing, sneezing, etc.) are multiphase/turbulent jet flows containing respiratory droplets, which include fluids covering the entire inner surface of the related airways. Obviously, these droplets are in different sizes and can be either suspended or be falling down the jet due to their weights. In addition, various environmental factors, such as temperature, relative humidity, wind, weather, etc., affect the distribution of these droplets. Since they play very important roles in disease transmission, engineers and scientists study the mechanism of their dispersion, break-up, coalescence, and deformation experimentally or using computational fluid dynamics (CFD). In this way, they will be able to offer some valuable non-pharmacological solutions to prevent the transmission of pathogenic viruses, such as COVID-19. Previous studies have shown that respiratory exhalation flows produce multiphase/turbulent flows, which have almost the same temperature (having a high humidity), as the body. In this work, computational investigation of the effects of a corona effected body and its surrounding environmental conditions, using large eddy simulation (LES) approach, are thoroughly described. The ultimate goal is to develop a sound computer code, which will be able to simulate a turbulent/multiphase flow related to respiratory exhalations. The main innovations of this research would be studying the different effects of day and night on related social distancing. Thus, for the continuous phase (a compressible turbulent jet with high humidity, which is floating due to difference of its temperature with the surrounding environment; e.g. a plume-like flow) Eulerian representation is used, while Lagrangian one is used for the dispersed phase, such that a fluid particle's velocity and temperature are updated along their path line.

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Keywords COVID-19 · Disease transmission · Respiratory events · Multiphase flow · Turbulent jet flow · Large Eddy Simulation (LES)

1 Introduction

During the COVID-19 outbreak, it was found that the international community has so far failed to control and curb the outbreak; due to little knowledge of the dynamic properties of respiratory droplets. In addition, medical science realized its fundamental weakness in controlling and overcoming unknown infectious respiratory diseases. Mutation of SARS-CoV-2 in human body was more deadly in some countries, which has caused concern and confusion among physicians [1]. Experimental studies have shown that shelf life of COVID-19 on different surfaces varies according to its material, while it stays in air for three hours [2, 3]. The virus is transmitted through contact and distribution of respiratory droplets. In the contact process, the individual interacts directly with the infected one or indirectly touches contaminated surfaces. On the other hand, a collection of droplets are released by exhalation containing fluids within the respiratory system. Studies have shown that about 35% of patients are asymptomatic [3] and can transmit disease without awareness. According to recent studies, many active cases have been infected by asymptomatic carriers [4, 5]. As a result, some researchers believe that respiratory droplets lead to much of the transmission of infectious viruses [6–8]. They found that patients with SARS and flu spread virus into air in the form of aerosols [9]. Therefore, airborne respiratory droplets can play a significant role in the transmission of infectious respiratory diseases.

The mechanism of droplets' production includes various physical processes, e.g., fluid instability, breakup, and its conversion into droplets [10]. In addition, droplet dispersion is due to its initial momentum and environmental air current.

Fortunately, investigation of such physical phenomena is feasible using computational fluid dynamics (CFD) as a powerful tool. Therefore, this way many results can be obtained by accurate computational simulations.

2 Respiratory Droplets

Numerical studies have shown to be extremely effective in comprehension of virus transmission, prevention of deterioration of conditions resulting from pandemic COVID-19, and therefore development and updating public health regulations. Several experimental and numerical studies have been performed to better understand respiratory processes and the behavior of droplets [11–13]. Accordingly, the size of respiratory droplets is in different ranges [14, 15]. The dimensions of droplets affect their deposition both in external environment and inside human respiratory system. Larger droplets fall into ground within a limit of about one meter, while smaller droplets remain suspended in air at much greater distances. So far, various studies simulated respiratory processes of sneezing and coughing [16–24] or analyzed the exhaled flow due to breathing or talking [15, 25, 26]. According to experimental [27] and numerical [28] data, droplet size range has a critical value, i.e., larger droplets fall into ground due to gravity through a ballistic path, while fine droplets remain suspended in air. Respiratory exhalation transfer finer droplets up to certain distances (about 2 to 8 m). Therefore, the allowable limit for social distancing should be more than about 2.5 m. Thus, world health organization (WHO) must renew its relevant regulations regarding social distancing [29]. Every day, millions of airborne droplets enter bodies with inhalation, wherein deposition in respiratory systems depends on the size, density, shape, as well as breathing pattern of each individual [30]. The smaller the droplet, the deeper it can travel the human airways [31]. In addition, there are enzymes within respiratory tract and the surface of the eyes that act as cellular receptors for the SARS-CoV-2 [32]. Therefore, infected respiratory droplets should be prevented from reaching them. Perhaps one of the best ways to reduce disease transmission is using appropriate coatings to block the virus [33, 34]. In an outbreak of infectious respiratory diseases, isolated workwear for medical staff, plastic face shields, and face masks are known as personal protective equipment (PPE). Improving face mask performance for respiratory droplets filtration is the principal concern for increasing their effectiveness due to their essential role as a non-pharmacological method in controlling virus transmission [35]. According to previous researches, wearing a face mask reduces the risk of infecting influenza, SARS, and COVID-19 viruses by about 45%, 74%, and 96%, respectively [36].

2.1 Size

Droplets induced by respiratory events are in different sizes and are known to be non-Newtonian fluids. Mucosa is viscoelastic and significantly affects size distribution and number of respiratory droplets [37]. According to previous analytical [38] and experimental [39] studies, the diameter range of respiratory droplets is between 1 and 2000 μm. Table 1 shows the size distribution of respiratory droplets in sneezing, coughing, and talking. As can be seen, sneezing produces more droplets than coughing or talking, i.e., the resulting number of droplets is approximately 200 times that of coughing and about 4,000 times that of talking. Furthermore, the most number of droplets are in the range 2–40 μm in all three phenomena.

In a healthy individual, average diameters of droplets during coughing and talking are 13.5 and 16 μm, respectively [40]. In addition, the lifetime of droplets varies according to their sizes (lifetime refers to a period when droplets do not evaporate or change phase and are suspended in the air at their actual size). According to Ref. [39], the time to eliminate 90% of droplets (which may carry a virus or bacteria) in a closed environment with still air is between 30 and 60 min. Moreover, droplets larger than 8 μm in diameter disappear in 20 min, while droplets larger than 4 μm disappear in 90 min. Nevertheless, smaller droplets can live longer (up to about 30 h), but in the

Table 1 Size distribution of droplets in sneezing, coughing, and talking; Duguid, JP, The size and the duration of air-carriage of respiratory droplets and droplet-nuclei, epidemiology & infection, 44, 6, 471–479, reproduced with permission [39]

Droplet diameter in μm	One sneeze	One cough	Talk
1–2	26,000	50	1
2–4	160,000	290	13
4–8	350,000	970	52
8–16	280,000	1,600	78
16–24	97,000	870	40
24–32	37,000	420	24
32–40	17,000	240	12
40–50	9,000	110	6
50–75	10,000	140	7
75–100	4,500	85	5
100–125	2,500	48	4
125–150	1,800	38	3
150–200	2,000	35	2
200–250	1,400	29	1
250–500	2,100	34	3
500–1000	1,000	12	1
1000–2000	140	2	0
Approx. Total	1,000,000	5,000	250

presence of airflow, e.g., a fan, droplet lifetime becomes much shorter. In severe exhalation processes, such as sneezing, fluid may break up and turn into droplets outside the respiratory tract [41]. According to Fig. 1, droplets are in the form of sheets. Then, the sheets are fragmented and formed into strands. Due to viscoelasticity, in some areas of these filaments density is higher, and mucosa turns into spherical granules and then separates from filaments. Therefore, viscoelasticity delays droplets breakup and thus, it affects its size distribution and also the dimensions of the smallest droplets downstream.

2.2 Formation

The high velocity of exhaled air causes atomization of saliva and mucosa in mouth and nose, leading to droplet formation [42]. Mucosa becomes unstable due to the existing shear force in the flow. The lung wall is also elastic, which is effective in causing this instability [43]. All three known Kelvin–Helmholtz, Rayleigh–Taylor, and Plateau–Rayleigh instabilities occur sequentially in exhaled respiratory jets. As shown in Fig. 2, a jet of liquid (thin sputum sheet) issues into the ambient air from the mouth leading to droplet formation. Then, droplets under Rayleigh–Taylor instability burst and form smaller droplets of different sizes due to Plateau–Rayleigh instability [44].

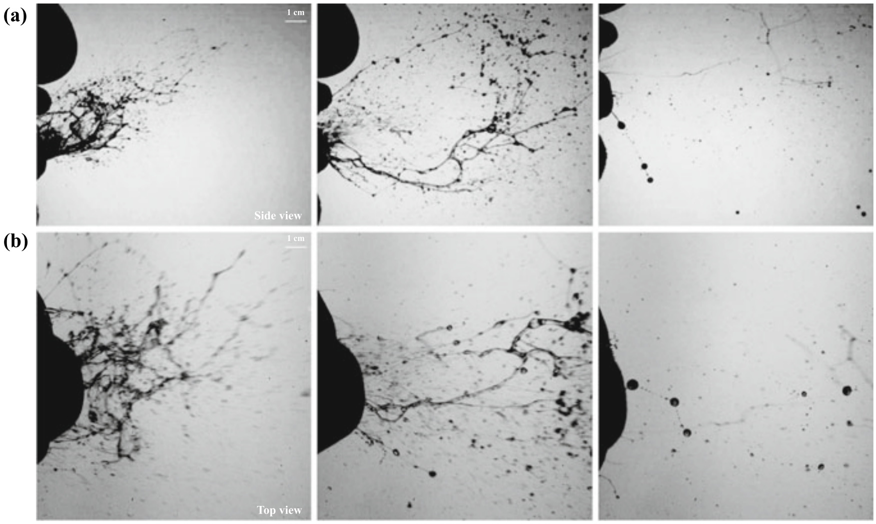


Fig. 1 Image of respiratory droplets' formation by non-Newtonian saliva in process of sneezing: **a** image from the side and **b** image from above the person's head; Reprinted by permission from Springer Nature: Springer Nature, experiments in fluids, visualization of sneeze ejecta: steps of fluid fragmentation leading to respiratory droplets, B. E. Scharfman et al. Copyright (2016) [41]

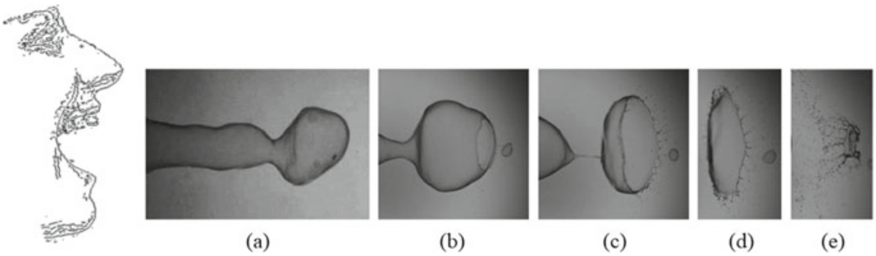


Fig. 2 Various stages of respiratory droplets' breakup: **a** instability occurs when a sheet of mucus comes out of mouth, **b** droplet formation by Kelvin–Helmholtz instability, **c** rupture of droplet due to Rayleigh–Taylor instability; **d** effect of surface tension and turning into smaller droplets due to Plateau–Rayleigh instability; Reproduced from M. Vadivukkarasan, K. Dhivyaraja, and M. V. Panchagnula, "Breakup morphology of expelled respiratory liquid: from the perspective of hydrodynamic instabilities," *Phys. Fluids*, Vol. 32, No. 9, pp. 094101, 2020, with the permission of AIP publishing [44]

Eventually, fluid breaks up and turns into droplets of various sizes, which move out of the respiratory tract. Breakup of droplets and their fragmentation in a viscoelastic fluid occur later than Newtonian fluid, having narrower and longer strings [45].

Liquid menisci blockage inside bronchus causes fluid to split and moves inside it. This fluid decomposes to smaller droplets. Factors affecting formation of droplets

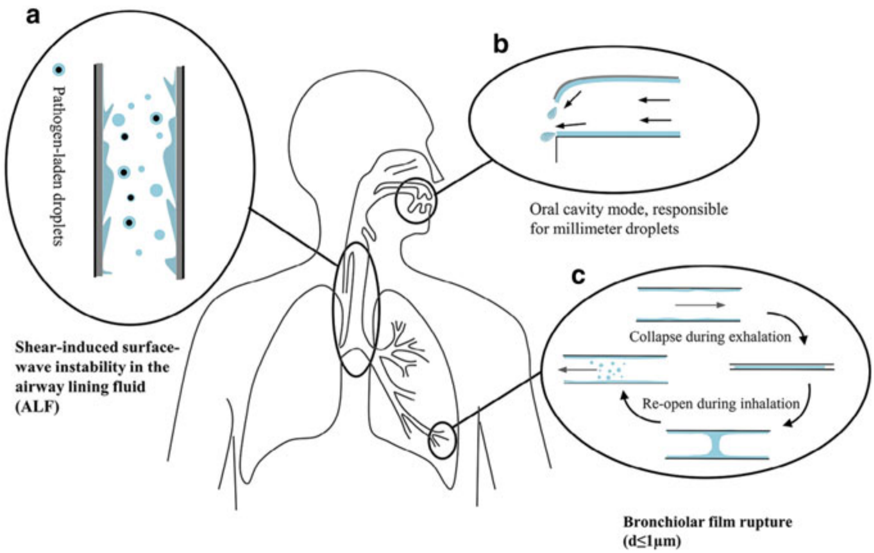


Fig. 3 Production of droplets within respiratory tract **a** instability of the fluid covering surface of airway, **b** atomization in mouth, and **c** rupture of fluid film in bronchi; Reprinted from airborne spread of infectious agents in the indoor environment, 44, Jianjian Wei, Yuguo Li, American Journal of Infection Control, S102-S108, Copyright (2016), with permission from Elsevier [47]

inside bronchus are: mucosa thickness covering its inner surface, menisci initial thickness, and capillary number ($\mu V/\sigma$, where μ is dynamic viscosity of the viscoelastic fluid, V is characteristic velocity, and σ is surface tension). There is a critical capillary number for menisci in equilibrium. When it is greater than its critical value and gradually increases, the fluid mass becomes smaller, leading to droplet formation even in normal breathing [46]. As shown in Fig. 3, bronchi are narrow tubes at the end of respiratory tract and are covered by a liquid film on their inner surface.

Breathing is a wave process (inhaling and exhaling). In exhalation, walls of bronchi coalesce and during inhalation they open up. As their walls move away from each other, liquid film forms the meniscus and droplets in the size of $d \leq 1\ \mu m$ [47]. After meniscus formation, severe stress is applied to flexible walls of bronchus, leading to damaging epithelial cells (cells on the surface of various organs, acting as protective barriers and preventing viruses from entering the body); thus, in infected people, it can cause death. In post-coalescence, stresses on bronchial walls are 300–600% higher than in pre-coalescence, which is a newly found factor in pulmonary cell disorder [48].

3 Aerodynamics of Droplets Induced by Respiratory Events

Respiratory exhalation is a multiphase turbulent flow wherein respiratory droplets of various sizes are suspended [16]. Temperature, humidity, and velocity of respiratory clouds are different from the environment in which it is emitted. Besides, droplets fall out of a respiratory cloud when their speed becomes slower than the cloud. As mentioned earlier, respiratory droplets of infected persons not only settle on adjacent surfaces and the objects they touch, but a significant number of them remain suspended in air for hours [49]. At short distances from the source, i.e., less than about 1.5 m, droplets smaller than 10 μm are immediately inhaled in a short time by susceptible individuals, and larger droplets settle on their bodies [50]. Numerical analysis of respiratory droplets, induced by breathing and talking [51], show that some letters generate more vortical structures than others during talking, leading to more droplet dispersion. Also, exhalation due to breathing is in the form of a puff, the distance it travels is related to time as $L\ t^{1/4}$, and is mixed with downstream ambient air. However, consecutive exhalation, such as talking, which is the result of several puffs, is a turbulent conical jet flow related to distance as $L\ t^{1/2}$. Of course, the respiratory patterns in different people are different due to various biological characteristics. For example, age or gender has little effect on average droplet size; but influences droplet concentration [52].

Therefore, the above points should be considered in numerical simulation of respiratory events to apply correct boundary and initial conditions. Various factors affect the transport and dispersion of respiratory droplets. For example, air temperature, humidity, wind, and ventilation are factors causing airborne droplets to evaporate or condensate. Further, these factors cause droplets to move in different directions or settle at various distances from the source.

3.1 Relative Humidity

Motion and evaporation of droplets depend on their size [53]. Relative humidity of environment is one of the efficient factors in this regard. Evaporation rate decreases at high relative humidity and leads to more droplet settling on surrounding surfaces due to their weight. Based on reference [54], more droplets remain suspended in air at low relative humidity and are more likely to be inhaled by other people. Small droplets (within 30 μm) are relatively light and follow an airflow pattern. While, relatively large droplets (100 μm) rapidly fall into ground and only 1% of them travel to a distance of about 2 m. Finally, relatively medium size droplets with a diameter of 50 μm travel about 4 m.

Relative humidity is not very effective in evaporating small and large droplets. However, medium droplets are very sensitive to relative humidity. In addition, it has a significant effect on droplet deposition. Figure 4 shows size distribution at

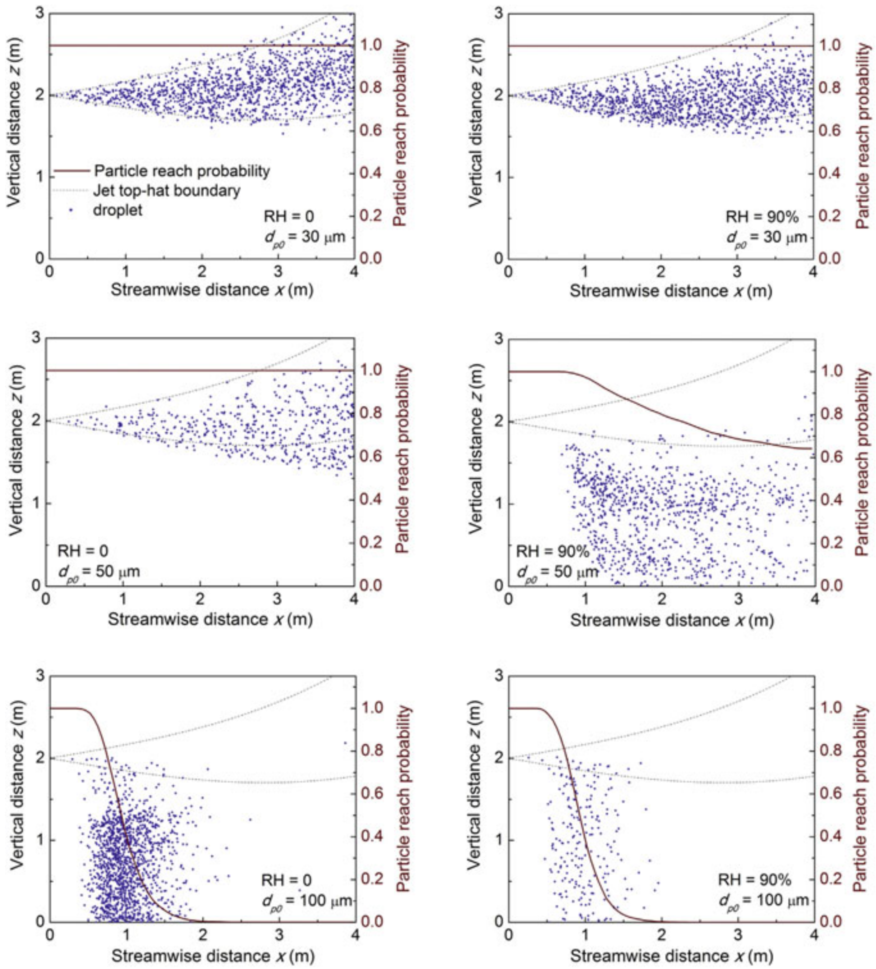


Fig. 4 The effect of relative humidity on motion of respiratory droplets having different sizes within a respiratory jet. Gray lines show jet boundary and dark red profile is its reach probability; Reprinted from enhanced spread of expiratory droplets by turbulence in a cough jet, 93, Jianjian Wei, Yuguo Li, Building and Environment, 86–96, Copyright (2015), with permission from Elsevier [54]

several distances upstream. Respiratory cloud has been simulated in both dry (about 0% relative humidity) and humid (about 90% relative humidity) environments to investigate droplet evaporation and displacement. The dark red line in Fig. 4 is a profile of reach probability of respiratory cloud.

Reach probability of respiratory cloud is defined as [54].

$$p(x) = \frac{N_{Tot} - N_{Dep}(x)}{N_{Tot}}, \tag{1}$$

where, N_{Tot} and N_{Dep} are total number of droplets released and deposited before reaching a specific streamwise distance x, respectively. As can be seen, small droplets are not affected by relative humidity and are dispersed inside the jet. However, with increasing relative humidity, about 40% of medium-size droplets travel a distance of about 4 m. Also, large droplets fall into ground at closer distances. By comparing two different relative humidities, it can be seen that the number of large droplets in relative humidity of about 90% is more limited. Because of high relative humidity, droplets evaporate very slowly and fall into ground immediately near the mouth. Relative humidity also affects the droplet nucleus' size, which is a solid residue of an evaporated respiratory droplet suspended in air and can be easily dispersed [55]. For a specific droplet, the size of a droplet nucleus at relative humidity of about 90% and about 25 °C temperature can be approximately 30% larger than the same droplet at a relative humidity less than about 65% at the same temperature [56].

3.2 Weather Condition

The local weather condition plays a significant role in infectious disease transmission. The distribution of respiratory droplets varies in different seasons. For instance, in autumn and in winter, the number of precipitated droplets on ground increases due to decreasing temperature and increasing relative humidity [57]. Therefore, social distancing should be implemented differently in various weather conditions [58]. In addition, increasing streamwise wind causes droplets to move farther downstream (up to about 7 m) and therefore, it pollutes more areas [59, 60]. Other researchers have also studied this effect, e.g. Ref. [61]. Such weather condition can lead to a turbulent flow in which more droplet dispersion is expected. In addition, when an infected individual moves in an environment with stagnant air, it can help spread of the virus (depending on his/her speed) [62]. Since the distance between passengers is inadequate in vehicles and the density of passengers in public transportation, especially airplanes, is very high [63, 64], the possibility of disease transmission is considerable [65]. For instance, droplets induced by a single cough are scattered in aircraft cabins and affect many passengers in a short period [66, 67]. Therefore, air-conditioning must be such that it keeps the indoor air fresh. Thus, droplet transfer in enclosed spaces in the presence of ventilation systems can be challenging in the field of aerosol sciences. This is because: the number of individuals, their body temperatures, and inadequate ventilation systems affect the dispersion of respiratory droplets [68].

3.3 Ventilation

Controlling concentration of virus-infected droplets in air is one of the most significant factors to prevent infectious diseases. Thus, ventilation strategies have a vital role in virus spread during respiratory processes and should be considered especially in designing a proper room for patients [69]. Based on numerical simulations [70], droplets with an initial diameter smaller than about 45 μm can move in air and remain suspended for more than about 6 min. Also, they are strongly influenced by flow pattern of ventilation systems. Since larger droplets cannot travel long distances with airflow and fall on different surfaces, the ventilation effect is negligible on droplets that settle quickly (short settling time). Numerical studies have shown that the location of ventilation also has significant effects on dispersion of droplets which therefore should especially be considered in the design of ventilation systems of medical centers [71, 72].

3.4 Ambient Temperature/Initial Speed of Exhalation Jet Effects

Exhalation is a jet flow with an initial velocity from a few meters per second (breathing and talking) to tens of meters per second (coughing and sneezing). As expiratory airspeed increases, droplets travel to farther distances. Note, large droplets are transferred about 6 m in sneezing (at a speed of about 50 m/s), about 2 m in coughing (at a speed of approximately 10 m/s), and about 1 m in breathing (at a speed of about 1 m/s). The value of the corresponding Reynolds number ($Re = VL/\upsilon$; where, V and L are characteristic velocity and length scales and υ is kinematic viscosity coefficient) is in the order of 10^2 to 10^5 (depending on certain respiratory process). Here, Reynolds number is based on the initial velocity of respiratory jet, the average diameter of mouth, and kinematic viscosity of airflow [17, 51, 60, 73]. Note, except in slow breathing, jet flow is a turbulent particulate multiphase flow, which is moist [16, 60, 74] with temperatures varying between about 34°C and 37°C. The speed of breathing, talking, coughing, and sneezing is about 0.5 to 100 m/s for an adult [51, 74–76].

Initial velocity affects the transverse dispersion of droplets. As it increases, larger areas in that direction become contaminated. Also, at a constant initial velocity, the smaller the mouth area, the farther a droplet travels [75]. Obviously, as ambient temperature increases, evaporation rate of droplets increases as well, i.e., droplets do not have enough time to diffuse or disperse in the environment [77].

A respiratory droplet is a viscoelastic fluid containing 89.6% water and 10.4% $NaCl$ [32]. Note, evaporation process continues until the entire liquid component is evaporated. The droplet nucleus is about 30% of its original diameter [21], but is still large enough to transfer the virus (coronavirus is within about 60 to 200 nm). Therefore, to optimize indoor air conditioning to provide fresh and virus-free air, the solid component of respiratory droplets should also be considered in the issue of temperature effect on evaporation rate. In addition to the effect of ambient temperature on evaporation of droplets and their dispersion, it should be considered

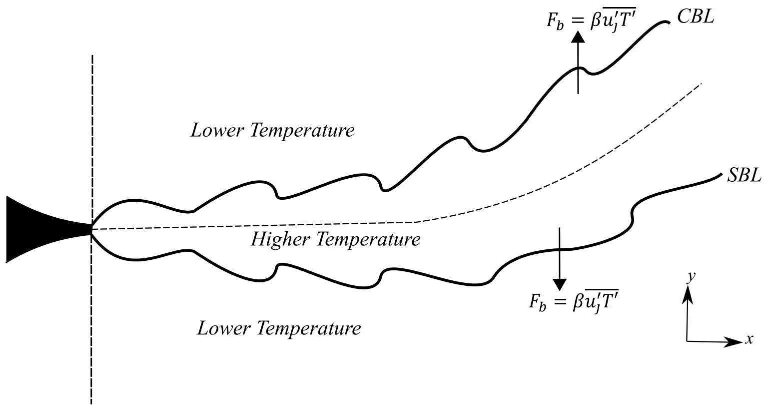


Fig. 5 The schematic of respiratory jet (dashed line is the centerline and $\boldsymbol{F_b}$ is corresponding heat flux, which is positive in CBL and negative in SBL)

that the temperature difference between exhalation and ambient air leads to deflection of jet path upwards (discussed later on).

Exhalation is a non-isothermal jet. According to Fig. 5, the upper part of the flow having higher temperature is located under the one with lower temperature. This situation is known as convective boundary layer (CBL), which is of course unstable.

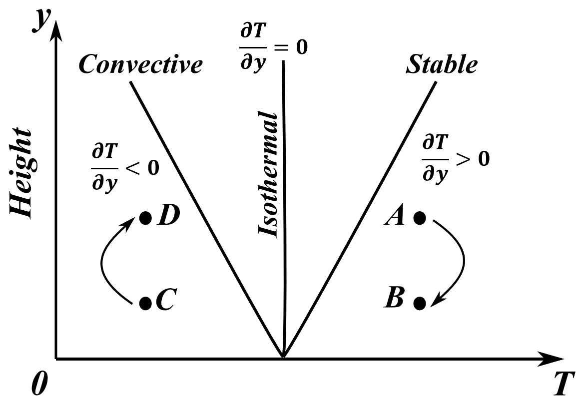
As discussed further down, light warm air tends to move upward and thus turbulent kinetic energy increases strengthening turbulent intensity and fluid mixing. Consequently, it is expected that the upper side of the jet experiences more entrainment (a process of fluid leaving/entering the jet).

In the lower part, it can be seen that light warm air is over cold one. As a result, it is a stable boundary layer (SBL), in which heat transfer is from the jet into the surrounding air. Therefore, buoyancy flux (F_b) is negative, and as a result, kinetic energy is reduced. In fact, in SBL, buoyancy prevents fluid elements from moving upward.

It is suspected that ambient air is also affected by temperature variations in an environment where surface temperature is different from its surrounding. For instance, during the day in an open area, where ground is warmer than air due to sunlight (or indoor space containing underfloor heating), the flow is unstable and heat transfer from a surface to air leads to vertical flux (increasing turbulence). This vertical flow cannot only affect expiration jet configuration, it also changes evaporation rate, deposition, and dispersion of droplets. In CBL condition, surface-deposited particles which have been re-suspended under shear stress are expected to move upward near the airways due to positive buoyancy. On the contrary, at night, when earth temperature is lower than the surrounding air, SBL condition suppresses turbulent flux in vertical direction and prevents the re-suspended particles from rising nearby the individual's head region (which could be otherwise re-inhaled).

Figure 6 can be used to discuss heat flux directions in more details. In SBL, when a fluid element moves from point A to point B, velocity becomes negative ($u_j' < 0$).

Fig. 6 The profile of different thermal stability conditions (note, in isothermal condition, buoyancy effect can be neglected)



However, warmer fluid enters a lower temperature region. Therefore, it increases the temperature of that area, and as a result, temperature fluctuation is positive there. Thus, heat flux is negative ($\overline{u'_j T'} < 0$) for SBL condition. On the other hand, in CBL, where fluid elements move from C (which is warmer) to D, $u'_j > 0$. Since fluid elements are warmer than other adjacent areas, $T' > 0$ and therefore $\overline{u'_j T'} > 0$ (positive heat flux).

4 Mathematical and Numerical Modeling

Many notable flows in fluid dynamics are multiphase, making it of particular importance to researchers and engineers. Appropriate numerical methods for simulating such flows depend on the specific physics involved. In general, multiphase flows are divided into two main categories: particulate and interfacial [78]. Interfacial multiphase flows are those in which the interface between discrete and continuous phases is large (e.g., flow of a relatively large gas bubble in a liquid boundary layer). In this case, most significant concern is accurate computation of motion and deformation of the interface. Whereas, regarding particulate multiphase flows, there exist many particles (gas, liquid, or solid) dispersed in the continuous phase (e.g., rain flow). Of course, the problem of respiratory events is a particulate multiphase flow.

Three different states may occur in such a flow, where fine droplets of solid, liquid, or gas (as discrete phase) are dispersed in a fluid of gas or liquid (as continuous phase) [78]. In the first case, void fraction (fraction of the volume occupied by dispersed phase) is notable. In this case, there are plenty of particles dispersed in continuous phase. Consequently, both particles and continuous phases are in local kinetic and temperature equilibrium, i.e., the relative velocity and temperature (between the two phases) can be neglected. So, flow is locally homogeneous and thus mixture method is applied. In this method, the molecular properties of the continuous phase are redefined, and then the problem is treated very similar to single-phase flows.

The second case is when void fraction is in the intermediate range. In this case, Eulerian-Eulerian method is employed, i.e., both continuous and discrete phases are simulated by Eulerian approach (discrete phase properties are also treated as a continuous fluid within the computational range).

The third case involves problems in which void fraction is low. For this situation, Eulerian approach is used for continuous phase, while Lagrangian for discrete one. Besides, if dispersed particles within a computational domain are not about the same (shape and size), Lagrangian approach uses a particle distribution function. Note, in all above three cases, problem must be addressed by statistical methods because, tracking all the droplets individually is impossible.

4.1 Coupling

Two-way coupling exists in respiratory flows, i.e., both phases affect each other. Coupling terms and their effects on mass fraction, momentum, and energy transport will be discussed further on. The mass transfer between droplet and water vapor appears in mass fraction transport equation. Besides, in momentum transport equation, the coupling term (F_{2way}) refers to the total surface forces of dispersed particles exert on continuous phase. Also, the whole energy, which transfers into continuous phase through convection or droplet evaporation, is E_{2way} in scalar temperature equation and is referred to as energy coupling.

4.2 Droplet Distribution

The distribution of droplets within respiratory clouds involves various droplet sizes and is called *polydisperse* distribution. In contrast, *monodisperse* distribution refers to problems in which the standard deviation of the mean droplet diameter is less than 10%.

Determination of particle distribution is performed in two methods, namely *continuous size* and *discrete size*. The features of each of these methods are explained in details in Ref. [79]. Several numerical studies have applied continuous size distribution of droplets using Rossin-Rammler distribution function [65, 73, 75, 80] and some others have used discrete size distribution method [24, 74, 81]. Since larger droplets do not have much opportunity to spread in the environment due to their rapid fall into ground or surrounding surfaces, they can be disregarded in numerical simulations [81]. Therefore, some simulations have only examined droplet dispersion in specified sizes [82, 83]. Exhalation is considered a dilute multiphase regime, in which particle–particle collision can be ignored [54, 84–86]. Consequently, it may be appropriate to only study the certain sizes (to save computational cost) instead of simulating the entire droplet size range. However, to the best of the authors' knowledge, it seems that further investigation is necessary on this assumption.

4.3 Modeling

Depending on Reynolds number, the flow regime is divided into three categories: laminar, transitional, and turbulent. In respiratory events, continuous phase is a turbulent jet flow exhaled to the outside environment and is described using Eulerian approach. Note, one of the most significant features of turbulent flows is existence of eddies (fluid particles of the same behavior) with different spatial and temporal dimensions. The largest eddies are in the flow length scale order and the smallest ones are known as Kolmogorov length scales [78]. The energy contained in eddies is transferred from the largest scales to the smallest ones (cascade of energy), which are responsible for dissipating turbulent kinetic energy.

The governing equations of continuous phase, which is buoyant due to temperature gradients, are as follows:

$$\frac{\partial u_i}{\partial x_i} = 0, \tag{2}$$

$$\frac{\partial \rho_v}{\partial t} + u_j \frac{\partial \rho_v}{\partial x_j} = D_v \frac{\partial^2 \rho_v}{\partial x_j \partial x_j} + Y_{2way}, \tag{3}$$

$$\frac{\partial u_i}{\partial t} + u_j \frac{\partial u_i}{\partial x_j} = -\frac{1}{\rho_c}\frac{\partial p}{\partial x_i} + \upsilon_c \frac{\partial^2 u_i}{\partial x_j \partial x_j} + g_i\left[1 - \beta_c\left(T - T_{ref}\right)\right] + F_{2way}, \tag{4}$$

$$\frac{\partial T}{\partial t} + u_j \frac{\partial T}{\partial x_j} = \frac{\upsilon_c}{Pr}\frac{\partial^2 T}{\partial x_j \partial x_j} + E_{2way}, \tag{5}$$

which are continuity, mass fraction, momentum, and temperature, respectively. In Eq's. (2) and (3),u_i, ρ_v, D_v, and Y_{2way} are velocity of continuous phase, density of water vapor, diffusion coefficient of water vapor, and mass transfer between droplet and water vapor, respectively. In addition, ρ_c, p, υ_c,g_i, β_c,T, F_{2way},Pr, and E_{2way} are continuous phase density, pressure, continuous phase kinematic viscosity, gravity, thermal expansion coefficient, temperature, the force of interaction between the two phases, Prandtl number (the ratio of momentum diffusivity to thermal diffusivity given by υ/α, where υ is kinematic viscosity and α is thermal diffiusivity), and energy coupling between them, respectively in Eq's. (4) and (5). To resolve the whole spectrum of eddies, direct numerical simulation (DNS) must be used because it does not implement any turbulence modeling. However, for engineering applications involving high Reynolds numbers, this approach is not possible with current computer resources. Note, computational cost increases with Reynolds number, because number of computational grid points grows with Reynolds number as [87].

$$N\ Re^{9/4}. \tag{6}$$

Instead of solving all length scales directly, different turbulence modeling can be implemented. Actually, in a turbulent flow, variables are decomposed into mean and fluctuative parts. For example, for a typical quantity, φ, one can write:

$$\phi = \overline{\phi} + \phi', \tag{7}$$

where, $\overline{\varphi}$ is the mean and $\varphi^{'}$ is the fluctuative parts of φ. If this relation is used in the governing equations and all terms are averaged, some new terms will be appeared. This is a *closure problem* because the number of equations and the number of unknowns are not equal. To solve this difficulty, different turbulence modelings are used. Depending on the averaging (or filtering) method used, various approaches are introduced. Two of the most famous approaches are Reynolds averaged Navier–Stokes (RANS) and large eddy simulation (LES). RANS is an eddy viscosity based model which averages in time. While, LES spatially filters Navire-Stokes equations, i.e., it resolves large eddies and models smaller ones. However, there are some other approaches, e.g., unsteady RANS (URANS), very large eddy simulation (VLES), and detached eddy simulation (DES), which have their own pros and cons and can be applied based on flow properties and the complexity of the problem [88]. Choosing the right approach for solving the continuous phase in two-phase flow problems has a significant effect on the discrete phase, since turbulent flow has significant effects on droplet dispersion or deposition [82]. For example, RANS does not resolve eddy motions and predicts only moderate droplet dispersion, while LES or DNS can identify and solve eddy structures containing energy in a turbulent flow [89]. As a result, they simulate the scattering and movement of droplets within a turbulent flow more accurately. In LES, a flow variable is defined as follows:

$$\phi(x, t) = \overline{\phi}(x, t) + \phi'(x, t). \tag{8}$$

Obviously, both mean and fluctuating parts are functions of time and space. In this approach, the effects of large eddies are solved directly by filtered Navier–Stokes equations. This is performed by filtering turbulent fluctuations and eliminating small spatial scales. One of the most important parameters in LES is filter width, which is defined as:

$$\Delta = \sqrt[3]{\Delta x \Delta y \Delta z}, \tag{9}$$

where, Δx, Δy, and Δz are the smallest computational grid size in x, y, and z directions, respectively. The choice of filter width depends on the problem and should be such that it captures about 80% of turbulent kinetic energy of the flow. It has the same order as the size of smallest eddies resolved in the flow. That is, scales larger than Δ are solved directly and smaller ones are modeled by sub-grid scale (SGS) models. The filtering operator is used to obtain large-scale components as [90].

$$\overline{\phi}(x,t) = \oint \phi(x-r,t)G(r,x)dr, \tag{10}$$

where, G is a filter function satisfying the following condition.

$$\oint G(r,x)dr = 1. \tag{11}$$

Some of the well-known filter functions that are mostly used in solving turbulent problems are Gaussian, box, and sharp.

The filtered continuity, mass fraction, momentum, and temperature transport equations are:

$$\frac{\partial \overline{u}_i}{\partial x_i} = 0, \tag{12}$$

$$\frac{\partial \overline{u}_i}{\partial t} + \overline{u}_j \frac{\partial \overline{u}_i}{\partial x_j} = -\frac{1}{\rho_c}\frac{\partial \overline{p}}{\partial x_i} + \upsilon_c \frac{\partial^2 \overline{u}_i}{\partial x_j \partial x_j} - \frac{1}{\rho_c}\frac{\partial \tau_{ij}^R}{\partial x_j} + g_i\left[1 - \beta_c\left(\overline{T} - T_{ref}\right)\right] + \overline{F}_{2way}, \tag{13}$$

$$\frac{\partial \overline{T}}{\partial t} + \overline{u}_j \frac{\partial \overline{T}}{\partial x_j} = \frac{\upsilon_c}{Pr}\frac{\partial^2 \overline{T}}{\partial x_j \partial x_j} - \frac{\partial \Theta_j}{\partial x_j} + \overline{E}_{2way}, \tag{14}$$

$$\frac{\partial \overline{\rho}_v}{\partial t} + \overline{u}_j \frac{\partial \overline{\rho}_v}{\partial x_j} = \frac{\partial}{\partial x_j}\left[\left(D_v + \frac{\upsilon_{SGS}}{Sc_{SGS}}\right)\frac{\partial \overline{\rho}_v}{\partial x_j}\right] + \overline{Y}_{2way}, \tag{15}$$

where, $\overline{u}_i$, $\overline{\rho}_v$, $\overline{p}$, and $\overline{T}$ are filtered velocity, water vapor density, pressure, and temperature, respectively. Note, in Eq. (15), υ_{SGS} is SGS turbulent viscosity and Sc_{SGS} (constant [91]) is turbulent Schmidt number. While, in Eq's. (13) and (14) two new unknown variables appear known as the SGS stress tensor,τ_{ij}^R, and turbulent heat flux, Θ_j defined as:

$$\tau_{ij}^R = \overline{u_i u_j} - \overline{u}_i \overline{u}_j, \tag{16}$$

$$\Theta_j = \overline{u_j T} - \overline{u}_j \overline{T}. \tag{17}$$

Smagorinsky, WALE, One-equation eddy are some popular models for the SGS stress term (τ_{ij}^R). In addition, turbulent heat flux model can be divided into three main categories: eddy thermal diffusivity, tensor thermal diffusivity, and mixed model, where, eddy thermal diffusivity model is one of the most popular ones to obtain heat flux (Θ_j) by introducing SGS Prandtl number, Pr_{SGS} [92].

Various numerical approaches are used to deal with the discrete phase, including Eulerian or Lagrangian. With the help of Lagrangian approach, properties, such as velocity, are updated along the path of each droplet [79]. In this approach, the locations of droplets are calculated by *point-force* or *resolved-surface* methods. In the second method, the integral form of momentum equation is used around the droplet leading to the force applied to it. Then, using Newton second law (Lagrangian form) leads to obtaining its location. This method requires an extremely precise grid around each droplet and thus is impossible to use in dense cases.

In point-force method, each droplet is treated individually, i.e., droplet is defined at a single point. The trajectory of each droplet is calculated by:

$$\frac{d\overline{x}_{d,l}}{dt} = \overline{u}_{d,l}, \tag{18}$$

(in Lagrangian frame). In Eq. (18), $\overline{x}_{d,l}$ and $\overline{u}_{d,l}$ are resolved location and velocity of droplet, respectively. In addition, momentum, temperature, and mass transfer (due to phase change) equations for a droplet are:

$$\rho_d V_{d,l} \frac{d\overline{u}_{d,l}}{dt} = F_{body} + F_{surf}, \tag{19}$$

$$\rho_d c_{p,d} V_{d,l} \frac{d\overline{T}_{d,l}}{dt} = c_{p,c} \overline{T}_{d,l} \frac{dm_{d,l}}{dt} + h_m A_{d,l} \left[\overline{T}(x_l, t) - \overline{T}_{d,l} \right], \tag{20}$$

$$\frac{dm_{d,l}}{dt} = -\frac{m_{d,l} Sh}{3\tau_p Sc} \ln\left(\frac{1-\rho_c}{1-\rho_d} \right), \tag{21}$$

where,ρ_d, $V_{d,l}$, c_{p_d}, $A_{d,l}$, $m_{d,l}$, and $\overline{T}_{d,l}$ are density, volume, specific heat capacity, area, mass, and filtered temperature of droplet$l$. In temperature transport equation, $c_{p,c}$ and $\overline{T}(x_l, t)$ are specific heat capacity and filtered temperature of the continuous phase at droplet location. In Eq. (21), Sh is Sherwood number, Sc is Schmidt number, and τ_p is droplet relaxation time. These parameters are given by $Sh = 2 + 0.6Re_d^{1/2} Sc^{1/3}$, $Sc = \mu_c / \rho_c D_\nu$, and $\tau_p = \rho_d d_i^2 / 18\mu_c$, where d_i and μ_c are droplet diameter and dynamic viscosity of continuous phase, respectively. Also, Re_d is droplets' Reynolds number defined in Eq. (25). Ranz-Marshall closed Eq's. (20) and (21) by approximating heat transfer coefficient,h_m, and Sherwood number [74]. Detailed information about Eq's. (20) and (21) can be found in Ref. [93]. In momentum Eq. (19), the first term on the right-hand side is body force, which is gravity in respiratory problems as:

$$F_{body} = \left(\rho_{d,l} - \rho_c \right) V_{d,l} g. \tag{22}$$

The second term in that equation shows the surface forces proportional to the area of the droplet. In general, this force is the sum of forces like drag, lift, apparent mass, Basset, etc. Thus:

$$F_{surf} = \sum_{n=1}^{N_{drop}} F_{surf,n} = F_D + F_L + F_A + F_B, \tag{23}$$

where, N_{drop} is the number of droplets. The first term on right-hand side of this equation is drag force obtained as:

$$F_{D,l} = \frac{\rho_c \pi d_l^2 C_{D,l}}{8} \left(\overline{u}_l - \overline{u}_{d,l}\right)\left|\overline{u}_l - \overline{u}_{d,l}\right|. \tag{24}$$

The drag coefficient $C_{D,l}$ is calculated using droplet Reynolds number, as:

$$Re_{d,l} = \frac{\rho_c d_l \left|\overline{u}_l - \overline{u}_{d,l}\right|}{\mu_c}, \tag{25}$$

$$C_{D,l} = \begin{cases} \frac{24}{Re_{d,l}}, \; Re_{d,l} \leq 1 \\ \frac{24}{Re_{d,l}}\left(1 + 0.15 Re_{d,l}^{0.687}\right), \; 1 < Re_{d,l} \leq 1000 \\ 0.44, \; Re_{d,l} > 1000. \end{cases} \tag{26}$$

The other terms on right-hand side of Eq. (23) are lift force (F_L), apparent mass force (F_A); due to acceleration of fluid around the droplet, and Basset force (F_B); due to unsteady history effect (wake behind droplet), respectively. All these forces can be neglected due to large density ratio of droplets and air [53, 71, 94, 95].

5 Summary

Respiratory events are multiphase turbulent jet flows which contain a cloud as continuous phase and droplets as discrete phase. Respiratory droplets are formed by physical processes, such as atomization, shear force, fluid instability, and breakup. They come in a wide range of sizes that can carry coronavirus within them. Large droplets fall into ground by ballistic motion to a distance of fewer than about 2 m, but tiny droplets remain in air and disperse. Transmission by respiratory droplets is one of the main ways of respiratory disease contagion. Engineers play an important role in reducing or even preventing spread of this disease by studying how droplets spread out, using CFD. This way, the continuous phase is modeled by an Eulerian approach solving Navier–Stokes equations for a non-isothermal flow. For the discrete phase however, methods such as point-force Lagrangian is employed. Since droplets are present in different sizes within respiratory cloud, their distribution is polydispersed and is implemented by methods such as Rosin–Rammler. Modeling respiratory events using Eulerian–Lagrangian method, droplet dispersion, factors affecting its transmission/evaporation/deposition, and the effects of ventilation system have been presented in this chapter.

6 Future Outlook

The daily confirmed COVID-19 cases are still high and extensive researches are still being conducted both numerically and experimentally. However, some important features are still receiving less attention. In this regard, some examples include determination of more precise boundary conditions for virus droplets distribution at the mouth exit, the possibility of secondary atomization of droplets after exhalation, differences between related liquid particles and their dispersion rates for healthy and sick individuals, and different human body features in healthy/unhealthy cases. On the other hand, considering more realistic non-Newtonian (viscoelastic) droplets can be an important issue to be studied. Such topics and much more can be considered in future numerical simulations, in order to achieve more accurate results.

References

1. Yao, H., et al.: Patient-derived mutations impact pathogenicity of SARS-CoV-2. CELL-D-20-01124 (2020)
2. Zhou, Y., Ji, S.: Experimental and numerical study on the transport of droplet aerosols generated by occupants in a fever clinic. Build. Environ. **187**, 107402 (2021)
3. Verma, S., Dhanak, M., Frankenfield, J.: Visualizing the effectiveness of face masks in obstructing respiratory jets. Phys. Fluids **32**(6), 61708 (2020)
4. Asadi, S., Bouvier, N., Wexler, A.S., Ristenpart, W.D.: The coronavirus pandemic and aerosols : does COVID-19 transmit via expiratory particles ? Taylor Fr. (2020)
5. Li, R., et al.: Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2). Science (80-.) **368**(6490), 489–493 (2020)
6. Dwosh, H.A., Hong, H.H.L., Austgarden, D., Herman, S., Schabas, R.: Identification and containment of an outbreak of SARS in a community hospital. CMAJ **168**(11), 1415–1420 (2003)
7. Seto, W., et al.: Effectiveness of precautions against droplets and contact in prevention of nosocomial transmission of severe acute respiratory syndrome (SARS). Lancet **361**(9368), 1519–1520 (2003)
8. Beggs, C.B.: The airborne transmission of infection in hospital buildings: fact or fiction? Indoor Built Environ. **12**(1–2), 9–18 (2003)
9. Yan, J., et al.: Infectious virus in exhaled breath of symptomatic seasonal influenza cases from a college community. Proc. Natl. Acad. Sci. **115**(5), 1081–1086 (2018)
10. Jain, M., Prakash, R.S., Tomar, G., Ravikrishna, R.: Secondary breakup of a drop at moderate weber numbers. Proc. R. Soc. A Math. Phys. Eng. Sci. **471**(2177), 20140930 (2015)
11. Cummins, C., Ajayi, O., Mehendale, F., Gabl, R., Viola, I.M.: The dispersion of spherical droplets in source-sink flows and their relevance to the COVID-19 pandemic. Phys. Fluids **32**(8), 83302 (2020)
12. Weiss, P., Giddey, V., Meyer, D.W., Jenny, P.: Evaporating droplets in shear turbulence. Phys. Fluids **32**(7), 73305 (2020)
13. Wang, B., Wu, H., Wan, X.F.: Transport and fate of human expiratory droplets—A modeling approach. Phys. Fluids **32**(8), 83307 (2020)
14. Asadi, S., Wexler, A.S., Cappa, C.D., Barreda, S., Bouvier, N.M., Ristenpart, W.D.: Aerosol emission and superemission during human speech increase with voice loudness. Sci. Rep. **9**(1), 1–10 (2019)
15. Gupta, J.K., Lin, C.H., Chen, Q.: Characterizing exhaled airflow from breathing and talking. Indoor Air **20**(1), 31–39 (2010)

16. Bourouiba, L., Dehandschoewercker, E., Bush, J.W.: Violent expiratory events : on coughing and sneezing. J. Fluid Mech. **745**, 537–563 (2014)
17. Busco, G., Yang, S.R., Seo, J., Hassan, Y.A.: Sneezing and asymptomatic virus transmission. Phys. Fluids **32**(7), 73309 (2020)
18. Diwan, S.S., Ravichandran, S., Govindarajan, R., Narasimha, R.: Understanding transmission dynamics of COVID-19-type infections by direct numerical simulations of cough/sneeze flows. Trans. Indian Natl. Acad. Eng. **5**, 255–261 (2020)
19. Dudalski, N., Mohamed, A., Mubareka, S., Bi, R., Zhang, C., Savory, E.: Experimental investigation of far-field human cough airflows from healthy and influenza-infected subjects. Indoor Air **30**(5), 966–977 (2020)
20. Dhand, R., Li, J.: Coughs and sneezes: their role in transmission of respiratory viral infections, including SARS-CoV-2. Am. J. Respir. Crit. Care Med. **202**(5), 651–659 (2020)
21. Chaudhuri, S., Basu, S., Kabi, P., Unni, V.R., Saha, A.: Modeling the role of respiratory droplets in Covid-19 type pandemics. Phys. Fluids **32**(6), 63309 (2020)
22. Dudalski, N.: Experimental measurements of human cough airflows from healthy subjects and those infected with respiratory viruses. Thesis, January (2019)
23. Gao, N., Niu, J.: Transient CFD simulation of the respiration process and inter-person exposure assessment. Build. Environ. **41**(9), 1214–1222 (2006)
24. Ng, C.S., Chong, K.L., Yang, R., Li, M., Verzicco, R., Lohse, D.: Growth of respiratory droplets in cold and humid air. Phys. Rev. Fluids **16**(5), 54303 (2021)
25. Almstrand, A.-C., et al.: Effect of airway opening on production of exhaled particles. J. Appl. Physiol. **108**(3), 584–588 (2010)
26. Huynh, K.N., Oliver, B.G., Stelzer, S., Rawlinson, W.D., Tovey, E.R.: A New method for sampling and detection of exhaled respiratory virus aerosols. Clin. Infect. Dis. **46**(1), 93–95 (2008)
27. Bourouiba, L.: Turbulent gas clouds and respiratory pathogen emissions: potential implications for reducing transmission of COVID-19. JAMA - J. Am. Med. Assoc. **323**(18), 1837–1838 (2020)
28. Kumar, V., et al.: On the utility of cloth facemasks for controlling ejecta during respiratory events. arXiv Prepr. arXiv2005.03444 (2020)
29. Shafaghi, A.H., Talabazar, F.R., Koşar, A., Ghorbani, M.: On the effect of the respiratory droplet generation condition on COVID-19 transmission. Fluids **5**(3), 113 (2020)
30. Heyder, J.: Deposition of inhaled particles in the human respiratory tract and consequences for regional targeting in respiratory drug delivery. Proc. Am. Thorac. Soc. **1**(4), 315–320 (2004)
31. Guzman, M.: Bioaerosol size effect in COVID-19 transmission (2020)
32. Feng, Y., Marchal, T., Sperry, T., Yi, H.: Influence of wind and relative humidity on the social distancing effectiveness to prevent COVID-19 airborne transmission : a numerical study. J. Aerosol Sci. 105585 (2020)
33. Riediker, M., Tsai, D.H.: Estimation of viral aerosol emissions from simulated individuals with asymptomatic to moderate coronavirus disease 2019. JAMA Netw. open **3**(7), e2013807 (2020)
34. Sakharov, A.S., Zhukov, K.: Study of an air curtain in the context of individual protection from exposure to coronavirus (SARS-CoV-2) contained in cough-generated fluid particles. Physics (College. Park. Md). **2**(3), 340–351 (2020)
35. Kumar, S., Lee, H.P.: The perspective of fluid flow behavior of respiratory droplets and aerosols through the facemasks in context of SARS-CoV-2. Phys. Fluids **32**(11), 111301 (2020)
36. Liang, M., et al.: Efficacy of face mask in preventing respiratory virus transmission: a systematic review and meta-analysis. Travel Med. Infect. Dis. **36**(March), 101751 (2020)
37. Anwarul Hasan, M.D., Lange, C.F., King, M.L.: Effect of artificial mucus properties on the characteristics of airborne bioaerosol droplets generated during simulated coughing. J. Nonnewton. Fluid Mech. **165**(21–22), 1431–1441 (2010)
38. Wells, W.F.: On air-borne infection: study II. Droplets and droplet nuclei. Am. J. Epidemiol. **20**(3), 611–618 (1934)

39. Duguid, J.: The size and the duration of air-carriage of respiratory droplets and droplet-nuclei. Epidemiol. Infect. **44**(6), 471–479 (1946)
40. Chao, C.Y.H., et al.: Characterization of expiration air jets and droplet size distributions immediately at the mouth opening. J. Aerosol Sci. **40**(2), 122–133 (2009)
41. Scharfman, B.E., Techet, A.H., Bush, J.W.M., Bourouiba, L.: Visualization of sneeze ejecta: steps of fluid fragmentation leading to respiratory droplets. Exp. Fluids **57**(2), 1–9 (2016)
42. Morawska, L.: Droplet fate in indoor environments, or can we prevent the spread of infection? Indoor Air **16**(5), 335–347 (2006)
43. Moriarty, J., Grotberg, J.: Flow-induced instabilities of a mucus-serous bilayer. J. Fluid Mech. **397**, 1–22 (1999)
44. Vadivukkarasan, M., Dhivyaraja, K., Panchagnula, M.V.: Breakup morphology of expelled respiratory liquid: from the perspective of hydrodynamic instabilities. Phys. Fluids **32**(9), 94101 (2020)
45. Joseph, D.D., Beavers, G.S., Funada, T.: Rayleigh-Taylor instability of viscoelastic drops at high weber numbers. J. Fluid Mech. **453**, 109–132 (2002)
46. Malashenko, A., Tsuda, A., Haber, S.: Propagation and breakup of liquid menisci and aerosol generation in small airways. J. Aerosol Med. Pulm. Drug Deliv. **22**(4), 341–353 (2009)
47. Wei, J., Li, Y.: Airborne spread of infectious agents in the indoor environment. Am. J. Infect. Control **44**(9), S102–S108 (2016)
48. Romano, F., Fujioka, H., Muradoglu, M., Grotberg, J.: Liquid plug formation in an airway closure model. Phys. Rev. Fluids **4**(9), 93103 (2019)
49. Booth, T.F., et al.: Detection of airborne severe acute respiratory syndrome (SARS) coronavirus and environmental contamination in SARS outbreak units. J. Infect. Dis. **191**(9), 1472–1477 (2005)
50. Liu, L., Li, Y., Nielsen, P.V., Wei, J., Jensen, R.L.: Short-range airborne transmission of expiratory droplets between two people. Indoor Air **27**(2), 452–462 (2017)
51. Abkarian, M., Mendez, S., Xue, N., Yang, F., Stone, H.A.: Puff trains in speaking produce long-range turbulent jet-like transport potentially relevant to asymptomatic spreading of viruses. arXiv Prepr. arXiv2006.10671 (2020)
52. Yang, S., Lee, G.W.M., Chen, C.M., Wu, C.C., Yu, K.P.: The size and concentration of droplets generated by coughing in human subjects. J. Aerosol Med. Depos. Clear. Eff. Lung **20**(4), 484–494 (2007)
53. Xie, X., Li, Y., Chwang, A., Ho, P., Seto, W.: How far droplets can move in indoor environments-revisiting the wells evaporation-falling curve. Indoor Air **17**(3), 211–225 (2007)
54. Wei, J., Li, Y.: Enhanced spread of expiratory droplets by turbulence in a cough jet. Build. Environ. **93**(P2), 86–96 (2015)
55. Verreault, D., Moineau, S., Duchaine, C.: Methods for sampling of airborne viruses. Microbiol. Mol. Biol. Rev. **72**(3), 413–444 (2008)
56. Liu, L., Wei, J., Li, Y., Ooi, A.: Evaporation and dispersion of respiratory droplets from coughing. Indoor Air **27**(1), 179–190 (2016)
57. Wang, H., Li, Z., Zhang, X., Zhu, L., Liu, Y., Wang, S.: The motion of respiratory droplets produced by coughing. Phys. Fluids **32**(12), 125102 (2020)
58. Maggiore, E., Tommasini, M., Ossi, P.M.: Propagation in outdoor environments of aerosol droplets produced by breath and light cough. Aerosol Sci. Technol. **55**(3), 340–351 (2020)
59. Li, H., Leong, F.Y., Xu, G., Ge, Z., Kang, C.W., Lim, K.H.: Dispersion of evaporating cough droplets in tropical outdoor environment. Phys. Fluids **32**(11), 113301 (2020)
60. Dbouk, T., Drikakis, D.: On coughing and airborne droplet transmission to humans. Phys. Fluids **32**(5), 53310 (2020)
61. Sandoval, M., Vergara, O.: Drops in the wind: their dispersion and COVID-19 implications. arXiv Prepr. arXiv2102.08277 (2021)
62. Kotb, H., Khalil, E.E.: Impact of sneezed and coughed droplets produced from a moving passenger on other passengers inside aircraft cabins. AIAA Propuls. Energy 2020 Forum, 3949 (2020)

63. Zhang, L., Li, Y.: Dispersion of coughed droplets in a fully-occupied high-speed rail cabin. Build. Environ. **47**(1), 58–66 (2012)
64. Bhatia, D., De Santis, A.: A preliminary numerical investigation of airborne droplet dispersion in aircraft cabins. Open J. Fluid Dyn. **10**(3), 198–207 (2020)
65. Zhang, Y., Li, J., Liu, M., Liu, J., Wang, C.: Experimental investigation of large-scale flow structures in an aircraft cabin mock-up. Build. Environ. **184**, 107224 (2020)
66. Gupta, J.K., Lin, C., Chen, Q.: Prediction of spatial and temporal distribution of expiratory droplets in an aircraft cabin. In: International High Performance Buildings Conference (2010)
67. Gupta, J.K., Lin, C.H., Chen, Q.: Transport of expiratory droplets in an aircraft cabin. Indoor Air **21**(1), 3–11 (2011)
68. Liu, H., He, S., Shen, L., Hong, J.: Simulation-based study of COVID-19 outbreak associated with air-conditioning in a restaurant. Phys. Fluids **33**(2), 23301 (2021)
69. Huang, J.M., Tsao, S.M.: The influence of air motion on bacteria removal in negative pressure isolation rooms. HVAC R Res. **11**(4), 563–585 (2005)
70. Wan, M P., Chao, C.Y.H., Ng, Y.D., Sze To, G.N., Yu, W.C.: Dispersion of expiratory droplets in a general hospital ward with ceiling mixing type mechanical ventilation system. Aerosol. Sci. Technol. **41**(3), 244–258 (2007)
71. Chen, C., Zhao, B.: Some questions on dispersion of human exhaled droplets in ventilation room: answers from numerical investigation. Indoor Air **20**(2), 95–111 (2010)
72. Ren, J., Wang, Y., Liu, Q., Liu, Y.: Numerical study of three ventilation strategies in a prefabricated COVID-19 inpatient ward. Build. Environ. **188**, 107467 (2021)
73. Dbouk, T., Drikakis, D.: On respiratory droplets and face masks. Phys. Fluids **32**(6), 63303 (2020)
74. Chong, K.L., Ng, C.S., Hori, N., Yang, R., Verzicco, R., Lohse, D.: Extended lifetime of respiratory droplets in a turbulent vapour puff and its implications on airborne disease transmission. Phys. Rev. Lett. **126**(31), 34502 (2021)
75. Pendar, M.R., Páscoa, J.C.: Numerical modeling of the distribution of virus carrying Saliva droplets during sneeze and cough. Phys. Fluids **32**(8) (2020)
76. Wilson, N., Norton, A., Young, F., Collins, D.: Airborne transmission of severe acute respiratory syndrome coronavirus-2 to healthcare workers: a narrative review, Anaesthesia (2020)
77. Dbouk, T., Drikakis, D.: Weather impact on airborne coronavirus survival. Phys. Fluids **32**(9), 93312 (2020)
78. Rahni, M.T., Karbaschi, M., Miller, R.: Computational methods for complex liquid-fluid interfaces (2015)
79. Crowe, C.T.: Multiphase Flow Handbook (2005)
80. Leonard, S., et al.: Reducing aerosol dispersion by high flow therapy in COVID-19: high resolution computational fluid dynamics simulations of particle behavior during high velocity nasal insufflation with a simple surgical mask. J. Am. Coll. Emerg. Physicians Open **1**(4), 578–591 (2020)
81. Li, H., et al.: Airborne dispersion of droplets during coughing: a physical model of viral transmission. Sci. Rep. **11**(1), 1–10 (2021)
82. Berrouk, A.S., Lai, A.C., Cheung, A.C., Wong, S.L.: Experimental measurements and large eddy simulation of expiratory droplet dispersion in a mechanically ventilated enclosure with thermal effects. Build. Environ. **45**(2), 371–379 (2010)
83. Zhang, Y., Feng, G., Kang, Z., Bi, Y., Cai, Y.: Numerical simulation of coughed droplets in conference room. Procedia Eng. **205**, 302–308 (2017)
84. Longest, P.W., Vinchurkar, S.: Validating CFD predictions of respiratory aerosol deposition: effects of upstream transition and turbulence. J. Biomech. **40**(2), 305–316 (2007)
85. Islam, M.S., Paul, G., Ong, H.X., Young, P.M., Gu, Y.T., Saha, S.C.: A Review of respiratory anatomical development, air flow characterization and particle deposition. Int. J. Environ. Res. Public Health **17**(2), 380 (2020)
86. Khare, P., Wang, S., Yang, V.: Modeling of finite-size droplets and particles in multiphase flows. Chinese J. Aeronaut. **28**(4), 974–982 (2015)

87. Durbin, P.A., Reif, B.P.: Statistical Theory and Modeling of Turbulence Flow, vol. 2. John Wiley & Sons (2011)
88. Wilcox, D.C.: Turbulence Modeling for CFD, vol. 2. DCW industries La Canada, CA (1998)
89. Vuorinen, V. et al.: Modelling aerosol transport and virus exposure with numerical simulations in relation to SARS-CoV-2 transmission by inhalation indoors. Saf. Sci. **130**(June), 104866 (2020)
90. Pope, S.B.: Turbulent Flows. IOP Publishing (2001)
91. Heidarinejad, G., Babaei, R.: Numerical investigation of electro hydrodynamics (EHD) enhanced water evaporation using large eddy simulation turbulent model. J. Electrostat. **77**, 76–87 (2015)
92. Wang, B.C., Yee, E., Bergstrom, D.J., Iida, O.: New dynamic subgrid-scale heat flux models for large-eddy simulation of thermal convection based on the general gradient giffusion hypothesis. J. Fluid Mech. **604**, 125–163 (2008)
93. Russo, E., Kuerten, J.G.M., Van Der Geld, C.W.M., Geurts, B.J.: Water droplet condensation and evaporation in turbulent channel flow. J. Fluid Mech. **749**(4), 666–700 (2014)
94. Fontes, D., Reyes, J., Ahmed, K., Kinzel, M.: A study of fluid dynamics and human physiology factors driving droplets dispersion from a human sneeze. Phys. Fluids **32**(11), 111904 (2020)
95. Wei, J., Li, Y.: Human cough as a two-stage jet and its role in particle transport. PLoS ONE **12**(1), e0169235 (2017)

COVID-19 Pandemic: Lessons Learned and Roadmap for the Future

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Abstract COVID-19 pandemic continues to teach us lessons. A wide range of recent technology advances and theoretical models, and developing new technology-driven paradigms were discussed in this book. In this final chapter, we have summarised and divided those technologies into six complementary parts: Technology-driven pandemic monitoring applications, Non-invasive COVID-19 detection and diagnostic systems, Decision-making analytics for COVID-19, Psychological and educational interventions in COVID-19 pandemic, Location intelligence and community resilience in pandemic situations, and Future directions and roadmaps. We present a summary of the findings discussed and a roadmap for the future.

Keywords Lesson learned · Roadmap · Future trends · COVID-19 · Pandemics

This book presented a wide range of recent technology advances and theoretical models on managing pandemic requirements and responses, and developing new technology-driven paradigms which are divided into the following six parts:

I. Technology-driven pandemic monitoring applications
II. Non-invasive COVID-19 detection and diagnostic systems
III. Decision-making analytics for COVID-19
IV. Psychological and educational interventions in COVID-19 pandemic
V. Location intelligence and community resilience in pandemic situations
VI. Future directions and roadmaps.

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By reviewing all contributions across various chapters of this book, in this final chapter, we present a summary of the findings discussed and a roadmap for the future.

During the last two years, we have witnessed several existing and new technologies being used to diagnose, monitor, track and manage COVID-19 worldwide. These include population surveillance tools, contact tracing technologies, sensors, smartphone apps, and machine learning tools [1–5].

The contact tracing tools appeared to have worked for the typical COVID-19 virus (prior to the emerging variants), possibly due to the lower infectivity and slower viral spread between infected and non-infected people. New COVID-19 viral variants exhibited growing transmissibility and increased reproduction ratio (R_0), making contact tracing technologies less effective. Therefore, these contact tracing technologies quickly reached their maximum potentials with the emergence of new variants. For that reason, future pandemic monitoring applications should be able to adapt faster to changes in the virus transmissibility and reproduction rate.

Many challenges have been pinpointed in various chapters of this book, including the following highlighted issues that have hindered the current worldwide pandemic responses the most [6]:

- Real-time epidemiological monitoring of asymptomatic population
- Data transparency and observability issues
- Data collection, modeling accuracy and consistency
- Privacy and (cyber)security implications

In response, the following approaches have recently been suggested in this book's chapters:

- Improved and optimized contact-tracing techniques (Chapters 3, 7, and 9)
- Utilizing ubiquitous geographic information system (GIS) and big data technologies (Chapters 15 and 26)
- Fingerprint testing, such as sewage and pooling testing (Chapter 26)
- Structural observability and identifiability.

The future of technology-driven pandemic monitoring systems will be data-driven and sensor-based [7]. These systems will utilize smart- and -intelligent materials [8] and secure end-to-end consumer-driven Internet-of-Things (IoT) gadgets to react much faster to the dynamic changes of infections in public health scenarios [9]. In addition, simple digital health technologies such as smartphone apps, wearables, telemedicine, and web-based tools will be used more commonly for integrated COVID-19 monitoring to improve disease surveillance (6–9). Machine learning models that have been applied to chest x-rays and Computed Tomography (CT)-scans to detect COVID-19 will further support disease monitoring, evaluation of disease progress, or response to treatment. While more advanced technologies such as advanced diagnostic biosensors and application of robots and drones have been proposed and tested in some high-income countries, these technologies need further development and testing before wider applications (10).

For monitoring COVID-19 at global, regional and country levels, digital vaccine passport could be the way forward (11). Machine learning tools for both short and long-term COVID-19 prediction and a global framework for assessment of the prediction models based on trust and transparency is recommended [16–19]. Furthermore, the future technology-based COVID-19 monitoring tools need to incorporate human behaviors such as physical activity, psychological conditions and other health indicators that could help in improving the health outcomes of people affected by COVID-19 [20–22].

During the current COVID-19 pandemic, numerous biological, clinical, and technology-based research endeavors focused on the detection, diagnosis, monitoring, management, and follow up on suspected or confirmed cases of COVID-19 infection [23, 24]. The main purpose of these research efforts was to support decision making, on the part of patients, clinicians, families, and/or public health authorities, across the globe. It should be highlighted that all those research works were being conducted while our knowledge of the coronaviruses, especially SARS-Cov2, was still developing over time. So, any outcome from a research study in a country was bearing the risk to become redundant, irrelevant, out-of-date, or obsolete in a few months. However, reflecting on the knowledge that the researchers and clinicians have gathered regarding detection, diagnosis, monitoring, management, and follow up on suspected or confirmed cases of 'any viral or bacterial condition', would be precious. Especially if we can leverage upon that knowledge and compare or combine it with what was collectively gathered during COVID-19 pandemic.

Essentially, for the detection of any viral or bacterial agent or its particles (protein or genetic code), one needs some form of 'sample', taken from the most appropriate part of the body, depending on where the infectious agent is living, replicating, or more concentrated [23]. The nature of SARS-Cov2 being a respiratory virus and its replication in the upper parts of the respiratory system (nose, throat) made it more convenient to provide a sample of some sort, either through bodily secretions from cough, saliva, or sputum, or taking swab from nose or throat. With any viral infection, sampling blood is also possible, both for detecting the virus, viral antigens, or immune response (i.e., antibodies) to the virus. During the current pandemic, both laboratory-based non-invasive diagnostic tests (like polymerase chain reaction [PCR]) and thereafter, home-based rapid antigen tests (RATs) were developed and became commercially available. However, both PCR and RAT also had their own challenges [25].

PCR tests, for example, were available in some countries only, inaccessible in a timely and consistent manner, resource-consuming (expensive, needing more trained human resource, with long waiting time for the results [sometime 4–5 days during peak testing times]), geographically restricted to specific testing sites, and impractical for home-testing. On the other hand, PCR results were reliable, acceptable, and automatically reportable to public health authorities, while being able to detect the virus earlier and for longer in the course of an active infection.

RAT tests, on the opposite, when became universally available, had the advantage of being obtainable more effortlessly for home-testing, with virtually no need for health professionals' involvement in the testing process and hence much less waiting time for results (10–15 min). Yet, RATs could not detect the virus as early or as longer in the course of active infection as PCRs, had less comparability especially in their specific sample requirements (saliva, nasal mucosal secretions, or breath), varied significantly in terms of instructions provided to perform the test, and ultimately, had to be self-reported by the individuals themselves to public health authorities. None of the RATs kits had any smartphone integration or digitization of their results.

Unavailability of, or unreliable access to, PCRs and RATs in some countries, especially from the developing world, was a major challenge. This issue pushed some countries to define alternative testing arrangements for 'ascertaining' the diagnosis of a COVID-19 case. In some countries, computed tomography (CT) scan of the chest became an acceptable alternative, to check for lung tissue changes compatible with COVID-19 infection, as a mean to confirm COVID-19 diagnosis. Some hot-spot countries went to define a set of diagnostic 'clinical criteria', based on patients' symptoms and signs, instead of laboratory investigations, to diagnose a COVID-19 case. The implications of this approach to non-invasive testing which does not rely on detecting the infective viral agent or its particles are that it should be considered a 'proxy' measure for confirming the diagnosis. So, like every diagnostic investigation, it would have its own sensitivity and specificity, and depending on the prevalence of COVID-19 in the population of interest, would eventually have different positive or negative predictive values.

For the future, the expectation is that novel pandemic response systems utilize non-invasive approaches for diagnosis to the fullest. Upcoming self-administered diagnostic investigations may give enough choice to patients for using a variety of samples to detect the infection, are equipped with multimedia instructions to help the individuals administer them optimally, can automatically record the results on a digital platform, and/or report the results to the required authorities. Using advanced artificial intelligence and machine learning algorithms, they can also estimate and report the likelihood of having the disease, its severity, and its contagiousness.

Furthermore, sensory devices which may come as typical features of future digital technologies, may incorporate breath or smell analyses for detecting viral fragments. The United States Food and Drug Administration (FDA) has already provided clearance to a diagnostic test that detects chemical compounds in breath samples associated with a SARS-CoV-2 infection [26].

Image processing is also an evolving field in the diagnosis of COVID-19 infection [27]. Future image-based diagnostic modalities (such as CT scan) may be equipped with artificial intelligence and machine learning algorithms to screen for potential cases of COVID-19 cases, provide likelihood of having the disease, and support clinicians' decision in optimizing triaging and resource allocation to patients who would benefit the most from available life-saving treatments.

Artificial intelligence (AI), machine learning, and big data analytics have shown promising results in cutting down the decision-making time in monitoring and diagnosing infections among the population [28]. These technologies have helped model the viral activities and spread, plus predict the severity of the infections, for improved and optimized decision making by policymakers and public health authorities.

The COVID-19 infection can cause a variety of clinical scenarios in terms of severity, from just an asymptomatic positive test result to full-blown septicaemia requiring advanced intensive care admission. The severity also varies significantly between age groups and ethnicities and depends on the availability of health system resources for monitoring, management, and follow up. Monitoring the progress of an active infection is key in the overall disease management. Also, monitoring after testing negative for COVID-19 is equally important to assess the chances of post-infection complications.

Monitoring devices, both invasive and non-invasive, at health facilities, and are expensive and human-resource intensive. Non-invasive disease monitoring technologies, instead, have been used as consumer-based options, for self-diagnosis, due to their ease of implementation among average consumers. These technologies use body-worn sensors, such as pulse-oximeters (for continuous SpO2 measurement), thermometers, heart-pulse monitors and electrocardiograms (ECG), and cuffless blood pressure devices [29], or as appropriate, electroencephalograms (EEG), or electromyograms (EMG) [30].

Future disease monitoring systems are expected to leverage these technologies. Moreover, artificial intelligence is expected to improve not only the detection and screening of an infection (and its corresponding disease), but may also help assessing the right treatment and management process, and to forecast the infectivity patterns. Furthermore, with the extended application of artificial intelligence in contact tracing or drug development, reduction in health professionals' workload is a legitimate expectation [31].

During the first waves of COVID-19, most countries went into mandatory lockdowns and as an alternative, resorted to online learning. The lack of face-to-face human interactions started negatively impacting many people, some more than others, which inevitably affected the psychological well-being of many unprepared for such an impact. The lesson learned from the twenty-first century's first pandemic includes the psychological vulnerabilities of isolation and lockdowns. Therefore, it's essential to know how to deal with such scenarios to withstand the next pandemic gracefully [32].

A systematic review and meta-analysis of sixty-five longitudinal cohort studies conducted during the first waves of COVID-19 pandemic in 2020, compared the mental health of various populations against those from before the pandemic. The results were significant and showed increasing mental health symptoms with large upsurges in depressive symptoms, particularly in those people with existing poor physical or mental health [33].

The uncertainty and unpredictability of COVID-19 pandemic, coupled with the physical distancing and associated lockdowns giving rise to mental health challenges, have proved to require sustainable adaptations of mental healthcare delivery systems in a proactive manner. The new mental healthcare delivery systems need to be designed and developed by clinicians and subject matter experts to mitigate disparities in healthcare provision, as a road map towards post-COVID-19 era [34].

Similar challenges were noticed across the education sector. Without the essential face-to-face interactions between students and instructors, online learning tools and techniques noticeable fell short for efficiency and the power to engage students to receive quality learning experiences.

The current literature suggests that the majority of the case studies and longitudinal research methodologies carried out in the last two years were highly geographically dependent and sectorized. These confounding factors present major obstacles in summarizing the learned lessons into universally applicable key outcomes to be used for similar future pandemic scenarios. However, majority of these studies point to the need to incorporate various learning analytics tools to aid pandemic-related requirements. These tools aim at easing obstacles, and meeting expectations for online and tele-education, which will become essential in future pandemics [35].

Lastly, we highlight the importance of geospatial information and location intelligence and community resilience in pandemic situations. Geospatial information plays an essential role in providing location dependent pandemic responses across multiple geographical domains and communities. Geospatial information and technologies are especially crucial for remote locations, urban, and rural resilience. Location intelligence is the methodology of deriving insights from location data to answer spatial questions, and it goes beyond simple data visualization on maps, to analyzing location data as an integral part of a business or societal problem. Therefore, the next pandemic response will be based on interdisciplinary analysis and provision of multisectoral expertise in using geospatial information and location intelligence to support better connection between communities and authorities to manage pandemics.

Several chapters in this book have shared and discussed different capabilities and techniques that have been developed and used in different jurisdictions to support the response to pandemic situations. In particular, the role that geospatial information and technological advancements have offered to predict and manage future scenarios. In this context, the following section will discuss some of the potential future directions.

From a location information perspective, COVID-19 pandemic has shown to the world the unequivocal importance and need for such information, enabling technologies, and clear and concise information that support authorities and decision-makers to keep their communities safe, and plan for the future and protect the most vulnerable in their jurisdictions. As such, location information, mapping and related analytical tools are widely used by health authorities, safety and emergency management departments and wider professional communities to support informed decisions.

The social and environmental factors, including population density and age, employment and lifestyle, all influence patterns of disease occurrence and prevalence. Managing a pandemic is inherently a geographic and location issue. In order to manage outbreaks, perform contact-tracing and enable a robust community response to stop the spread, spatial information is required, and location information is paramount. Geospatial information is crucial for informed social, economic, and environmental decision making – the three pillars of sustainable development. However, geospatial information is often a scarce resource, if it exists at all.

The COVID-19 pandemic is proving the need for a collaborative geospatial infrastructure that will help us better understand the crisis at hand at both local and global scales, as well as better prepare for future pandemics. The use of geospatial information and location intelligence and analytical tools, are important to support understanding the outbreak and its relationship to infrastructure, population, businesses and other location-based entities. Such information streams are important for monitoring, planning and managing the outbreaks and minimizing their impacts.

With the fast-changing societies and advancement in technologies, plus population growth, there is a growing need for real-time maps and location information, to track and share location data. As such, a geospatial-enabled platform, along with data analytics tools and solutions play a critical role in assisting the pandemic's front lines and keeping the general public informed and prepared. Geographic information systems (GIS) for example have always been a tool in managing the response to large-scale disasters by using location technology that helps us understand the situation at hand, develop a response and prepare a road to recovery. A spatial team of experts is of paramount importance to help create the maps, data, apps, analysis, and dashboards that are required for emergency management and resource allocation.

Since early stages of COVID-19 in 2020, there were extraordinary efforts around the globe where geospatial practitioners in many countries began to work together, by sharing information and analytical capabilities based on GIS tools. These endeavors helped us all grasp the situation at hand and enabled the decision-makers in their response to the COVID at local, national and global levels. These efforts have been on a global scale and as such, we have evolved into a world that supports connected and global analytical platforms. The COVID-19 pandemic has also demonstrated that in a highly interconnected social, economic, and natural environments, a highly contagious virus can become a global pandemic in no time [28].

One of the lessons that we have learned since the beginning of COVID-19, is that data need to be organized and managed via harmonized terms and definitions, using spatial data infrastructures (SDI) as a backbone at both local and national levels. Issues around core data, such as interoperability, common geographies, integration of statistics and geography, privacy and confidentiality and cybersecurity need to be addressed. Experiences during the pandemic, depicted in many parts of this book, tell us that when complex decisions are needed, there is no time to sign data custodian agreements or to integrate geospatial databases. In multiple chapters of this book, the need to access geospatial information that are effectively supported by an SDI as part of the national data infrastructure is shown. The geospatial information must be operational and provide access to all level of authorities. This situation can then be automated and improved by embedding a dynamic system for capturing and analyzing the data using latest technologies such as artificial intelligence using location intelligence.

This will ensure the most effective ways to assist future planning. With this planning, we can imagine a future where a multi-scale SDI is in place in most countries around the world. The maturity and adoption levels may be uneven across different countries but the core definitions and reference data are harmonized, with high interoperability and linkages with other data infrastructures and platforms. A diverse range and type of data contents can also come from established and new sources – including those from new technologies and from the crowd – with trusted provenance and quality indicator that protects individual and organizational privacy. The geospatial information of most data is preserved. The infrastructure and the contents are supported by sensible data governance regimes and appropriate cybersecurity measures. The supporting physical infrastructure is robust, in the face of an extreme event, and highly resilient in case of disruption.

With a solid data infrastructure in place and in operation, when the next global crisis occurs, new information can be readily managed and made widely available. New mobile and digital applications and solutions can be developed rapidly to meet the specific needs of future crises, allowing data to be used more effectively for a coordinated response and decision-making by different stakeholders, including the public. Information management protocols guide these stakeholders in an environment of information excess and where "infodemic" is widespread [36].

In the context of national and community resilience, geospatial information and location intelligence are critically significant for systemic and institutional preparedness to enable the country, government, and communities to mitigate hazards, adapt and recover from shocks or stresses. Such preparedness, adaption and recovery should be without compromising long-term development prospects of communities, cities, localities, regions, and countries. That means digital information, secure data storage of administrative information and an NSDI providing geospatial information that is accessible, authoritative, and sustainable. These are initiatives which must be led by the government for the benefit of all, with participation from civil societies, communities, private sector professionals, investors, and academics.

A major impediment to pandemic preparedness is often the weak street and postal address systems which precludes effective emergency response, contact tracing and monitoring of families and individuals for medical testing and follow-ups, vaccination programs, reliable reporting statistics, delivery and access to social benefits or similar efforts. To reduce risks associated with pandemics, geospatial data can be used in the following ways, to:

- Predict how the disease will spread, e.g., by identifying and analyzing places or routes frequented by many people in close proximity to one another;
- Prevent the spread of the disease, e.g., by identifying vulnerable areas based on population density, demographics (age) and/or income, and protecting them;
- Mitigate the spread of the disease, e.g. by tracing people who visited the same locations when infected;
- Strengthen preparedness, e.g., by adjusting the number of planned medical procedures in relation to the number of infections in a hospital's catchment area;
- Respond to the disease, e.g., by identifying optimal routes for testing or awareness campaigns; and
- Monitor and communicate the spread of the disease at different scales, e.g., infections by country or province, or more fine-grained by street block, event or building and even location of an infected individual.

In order to investigate and understand the actual spread of the disease, location-based information about the infected people and the places they visited is required. Information about such locations is often provided in the form of a residential address that needs to be converted into coordinates through geocoding based on geo-referenced address data.

In summary, geospatial information and location intelligence that helps to answer series of questions is useful for responding to pandemic challenges, such as locations of high risk of transmission, pinpointing the whereabout of vulnerable and infected people; and their movements over time [36].

References

1. Sharifrazi, D., et al.: Fusion of convolution neural network, support vector machine and Sobel filter for accurate detection of COVID-19 patients using X-ray images. Biomed. Signal Process. Control **68**, 102622 (2021)
2. Khozeimeh, F., et al.: Combining a convolutional neural network with autoencoders to predict the survival chance of COVID-19 patients. Sci. Rep. **11**(1), 1–18 (2021)
3. Chowdhury, N.K., et al.: Machine learning for detecting COVID-19 from cough sounds: an ensemble-based MCDM method. Comput. Biol. Med. 105405 (2022)
4. Asgharnezhad, H., et al.: Objective evaluation of deep uncertainty predictions for covid-19 detection. Sci. Rep. **12**(1), 1–11 (2022)
5. Aktar, S., et al.: Machine learning approach to predicting COVID-19 disease severity based on clinical blood test data: statistical analysis and model development. JMIR Med. Inform. **9**(4), e25884 (2021)
6. Alamo, T., Millán, P., Reina, D.G., Preciado, V.M., Giordano, G.: Challenges and future directions in pandemic control. IEEE Control Syst. Lett. **6**, 722–727 (2022). https://doi.org/10.1109/LCSYS.2021.3085700
7. Alamo, T., Reina, D.G., Gata, P.M., Preciado, V.M., Giordano, G.: Data-driven methods for present and future pandemics: monitoring, modelling and managing. Annu. Rev. Control. **52**, 448–464. ISSN 1367-5788. https://doi.org/10.1016/j.arcontrol.2021.05.003
8. Afroj, S., Britnell, L., Hasan, T., Andreeva, D.V., Novoselov, K.S., Karim, N.: Graphene-based technologies for tackling COVID-19 and future pandemics. Adv. Func. Mater. **31**(52), 16 (2021). https://doi.org/10.1002/adfm.202107407
9. Elansary, I., et al.: The future scope of internet of things for monitoring and prediction of COVID-19 patients. In: Digital Transformation and Emerging Technologies for Fighting COVID-19 Pandemic (2021)
10. Moses, J.C., et al.: Application of smartphone technologies in disease monitoring: a systematic review. In: Healthcare. Multidisciplinary Digital Publishing Institute (2021)
11. Islam, S.M.S., et al.: Mobile phone text-messaging interventions aimed to prevent cardiovascular diseases (Text2PreventCVD): systematic review and individual patient data meta-analysis. Open Heart **6**(2), e001017 (2019)
12. Islam, S., et al.: Validation and acceptability of a cuffless wrist-worn wearable blood pressure monitoring device among users and healthcare professionals: a mixed-method study. JMIR Mhealth Uhealth **7**(10), e14706 (2019)
13. Soron, T.R., et al.: The hope and hype of telepsychiatry during the COVID-19 pandemic. Lancet Psychiatry **7**(8), e50 (2020)
14. Khan, H., et al.: Smart technologies driven approaches to tackle COVID-19 pandemic: a review. 3 Biotech **11**(2), 1–22 (2021)
15. Sharif, A., et al.: A pragmatic approach to COVID-19 vaccine passport. BMJ Glob. Health **6**(10), e006956 (2021)
16. Alizadehsani, R., et al.: Uncertainty-aware semi-supervised method using large unlabeled and limited labeled COVID-19 Data. ACM Trans. Multimed. Comput. Commun. Appl. (TOMM) **17**(3s), 1–24 (2021)
17. Islam, S.M.S., Khosravi, A.: The need for a prediction model assessment framework. Lancet Glob. Health **9**(4), e404 (2021)

18. Satu, M., et al.: Short-term prediction of COVID-19 cases using machine learning models. Appl. Sci. **11**(9), 4266 (2021)
19. Abouzid, M., et al.: Influence of COVID-19 on lifestyle behaviors in the Middle East and North Africa Region: a survey of 5896 individuals. J. Transl. Med. **19**(1), 1 (2021)
20. Alizadehsani, R., et al.: Factors associated with mortality in hospitalized cardiovascular disease patients infected with COVID-19. In: Immunity, Inflammation and Disease (2022)
21. Ghozy, S., et al.: COVID-19 and physical inactivity: teetering on the edge of a deadlier pandemic? J. Glob. Health 11 (2021)
22. Rahman, M.A., et al.: COVID-19: Factors associated with psychological distress, fear, and coping strategies among community members across 17 countries. Glob. Health **17**(1), 1–19 (2021)
23. Rai, P., Kumar, B.K., Deekshit, V.K., Karunasagar, I., Karunasagar, I.: Detection technologies and recent developments in the diagnosis of COVID-19 infection. Appl. Microbiol. Biotechnol. **105**(2), 441–455 (2021)
24. Majumder, J., Minko, T.: Recent developments on therapeutic and diagnostic approaches for COVID-19. AAPS J. **23**(1), 14 (2021)
25. Boger, B., Fachi, M.M., Vilhena, R.O., Cobre, A.F., Tonin, F.S., Pontarolo, R.: Systematic review with meta-analysis of the accuracy of diagnostic tests for COVID-19. Am. J. Infect. Control **49**(1), 21–29 (2021)
26. FDA: Coronavirus (COVID-19) Update: FDA Authorizes First COVID-19 Diagnostic Test Using Breath Samples 2022 [14 April 2022]. https://www.fda.gov/news-events/press-announcements/coronavirus-covid-19-update-fda-authorizes-first-covid-19-diagnostic-test-using-breath-samples.
27. Alafif, T., Tehame, A.M., Bajaba, S., Barnawi, A., Zia, S.: Machine and deep learning towards COVID-19 diagnosis and treatment: survey, challenges, and future directions. Int. J. Environ. Res. Public Health **18**(3), 1117 (2021)
28. Swayamsiddha, S., Prashant, K., Shaw, D., Mohanty, C.: The prospective of Artificial Intelligence in COVID-19 Pandemic. Health Technol. (Berl). **11**(6), 1311–1320 (2021)
29. Mukkamala, R., Yavarimanesh, M., Natarajan, K., Hahn, J.-O., Kyriakoulis, K.G., Avolio, A.P., et al.: Evaluation of the accuracy of cuffless blood pressure measurement devices: challenges and proposals. Hypertension **78**(5), 1161–1167 (2021)
30. Guo, Y., Liu, X., Peng, S., Jiang, X., Xu, K., Chen, C., et al.: A review of wearable and unobtrusive sensing technologies for chronic disease management. Comput. Biol. Med. **129**, 104163 (2021)
31. Mohite, V., Vyas, K., Phadke, G., Rawtani, D.: Challenges and future aspects of COVID-19 monitoring and detection. In: Rawtani, D., Hussain, C.M., Khatri, N. (Eds.), COVID-19 in the Environment: Elsevier, pp. 131–150 (2022)
32. Armour, C., McGlinchey, E., Butter, S., et al.: The COVID-19 psychological wellbeing study: understanding the longitudinal psychosocial impact of the COVID-19 pandemic in the UK; a methodological overview paper. J. Psychopathol. Behav. Assess. **43**, 174–190 (2021). https://doi.org/10.1007/s10862-020-09841-4
33. Robinson, E., Sutin, A.R., Daly, M., Jones, A.: A systematic review and meta-analysis of longitudinal cohort studies comparing mental health before versus during the COVID-19 pandemic in 2020. J. Affect. Disord. **296**, 567–576 (2022). ISSN 0165-0327, https://doi.org/10.1016/j.jad.2021.09.098
34. Moreno, C., Wykes, T., Galderisi, Nordentoft, M., Crossley, N., Jones, N., Cannon, M., Correll, C.U., Byrne, L., Carr, S., Chen, E.Y.H., Gorwood, P., Johnson, S., Kärkkäinen, H., Krystal, J.H., Lee, J., Lieberman, J., López-Jaramillo, C., Männikkö, M., Phillips, M.R., Uchida, H., Vieta, E., Vita, A., Arango, C.: How mental health care should change as a consequence of the COVID-19 pandemic. Lancet Psychiatry **7**(9), 813–824 (2020). ISSN 2215-0366. https://doi.org/10.1016/S2215-0366(20)30307-2
35. Celik, I., Gedrimiene, E., Silvola, A., Muukkonen, H.: Response of learning analytics to the online education challenges during pandemic: Opportunities and key examples in higher education. Policy Futur. Educ. (2022). https://doi.org/10.1177/14782103221078401

36. Bell, K., Evtimov, V.: Land administration and authoritative geospatial information: lessons from disasters to support building resilience to pandemics. In: Rajabifard, A., Foliente, G., Paez, D. (Eds.), COVID-19 Pandemic, Geospatial Information, and Community Resilience: Global Applications and Lessons. CRC Press (2021). https://doi.org/10.1201/9781003181590