Studies in Computational Intelligence 933

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IoT in Healthcare and Ambient Assisted Living

Springer

Studies in Computational Intelligence

Volume 933

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ISSN 1860-949X ISSN 1860-9503 (electronic)
Studies in Computational Intelligence
ISBN 978-981-15-9896-8 ISBN 978-981-15-9897-5 (eBook)
https://doi.org/10.1007/978-981-15-9897-5

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Preface

The Internet of Things (IoT) includes the pervasive behaviour of cyber-physical systems that include sensing capabilities. These devices are connected to the Internet and support data transmission features. Nowadays, IoT architectures are used in the design and development of cost-effective systems for enhanced public health and well-being. Furthermore, IoT leads to numerous opportunities and advantages concerning the development of novel daily routine applications to support healthcare. IoT technologies are closely related to the healthcare context. IoT systems can provide ubiquitous and pervasive methods for healthcare monitoring using wireless communication technologies. Consequently, IoT is a practical approach to the design and development of novel healthcare methods. Using these architectures based on the most recent technology advancements enables the creation of innovative methods for the treatment of multiple diseases. Wearable devices are relevant pervasive technologies included in IoT ecosystems. The use of wearable technologies in the healthcare domain has increased in recent years. Numerous research activities include a wide range of wearable devices applied to healthcare. Ambient Assisted Living is a multi-disciplinary research domain which consists of an ecosystem of multiple types of sensors, microcontrollers, wireless communication technologies and software applications. In particular, Ambient Assisted Living incorporates the most recent technologies that can be used to increase the quality of life of older adults or disabled people. IoT for healthcare and Ambient Assisted Living require efficient methods, architectures, platforms, and intelligent algorithms to design novel solutions not only to improve public health and well-being but also to maintain people inside their home instead of been transferred to nursing homes.

This volume aims to present the current state of the art on IoT, healthcare and Ambient Assisted Living. The chapters of this book offer a transversal coverage on relevant related topics such as emerging IoT applications on healthcare, wearable devices and sensors for pervasive and personalized healthcare, smart homes, and Ambient Assisted Living. The editors have taken care to cover the breadth and depth of the subject, both qualitatively and quantitatively. Furthermore, this book synthesizes the existing body of knowledge and aims to be a reference not only to academics or engineers but also to healthcare professionals and organizations. The discussion on numerous key research topics will accelerate the progress and deployment of IoT in healthcare and Ambient Assisted Living. The included chapters aim to provide an essential background to support future research initiatives. The editors also have attempted to discuss the current trends and limitations related to the scope of the book. This book includes 17 chapters contributed by promising researchers located in 15 different countries. These countries include Australia, Belgium, Egypt, Greece, India, Iran, Italy, Malaysia, Mexico, Nigeria, Pakistan, Russia, Turkey, USA, and Ukraine.

We would like to thank the contributors of this book for their timely and positive response to the received review comments. Moreover, we acknowledge individuals who have helped us in this project. Last but not least, we thank Springer Publishing Team for their continuous supporting since the beginning stage to the production of this edited volume.

We sincerely hope that the chapters of this book can help future research studies not only in academics or engineering domain but also in the healthcare context.

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Acknowledgement VHCA received support from the Brazilian National Council for Research and Development (CNPq, Grant # 304315/2017-6 and #430274/2018-1).

About This Book

This book presents a coherent understanding of the state of the art of Internet of Things (IoT) from the perspective of the healthcare and Ambient Assisted Living (AAL) domain. IoT presents a set of hardware and software emerging technologies that can be used to a broad range of healthcare services for medical staff and patients to promote health and well-being in an effective and often pervasive manner. IoT solutions for healthcare and AAL require efficient methods, architectures, platforms, and intelligent algorithms to design and develop innovative systems not only for enhanced public health and well-being but also to maintain people inside their home instead of been transferred to nursing homes. The chapters of this book offer a transversal coverage on relevant related topics such as emerging IoT applications on healthcare, wearable devices and sensors for pervasive and personalized healthcare, smart homes, and Ambient Assisted Living. The editors have taken care to cover the breadth and depth of the subject, both qualitatively and quantitatively. Furthermore, this book synthesizes the existing body of knowledge and aims to be a reference not only to academics or engineers but also to healthcare professionals and organizations. The discussion on numerous key research topics will accelerate the progress and deployment of IoT in healthcare and Ambient Assisted Living. The included chapters aim to provide an essential background to support future research initiatives. This volume focus on the current trends and limitations related to the scope of the book.

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National Science Foundation, USA and Federation University, Australia and recently selected for AICTE-UKIERI Technical Leadership Development Programme for his research and academic contributions.

The Internet of Things for Healthcare: Applications, Selected Cases and Challenges

Rehab A. Rayan, Christos Tsagkaris, and Romash B. Iryna

1 Introduction

The Internet of Things (IoT) is a term that has numerous uses, technologies, standards, and programs. At its core, it is a network of things that are connected to the Internet. These things include IoT devices and physical objects equipped with IoT. Things and data are the starting point and the essence of what IoT means and allows doing. IoT devices and assets are equipped with electronic components and software to receive, sort, and share data.

The author of the term "Internet of Things" is Kevin Ashton. In the late 1990s, he studied radio frequency identification (RFID), a technology that allows small items of radio frequency tags to be attached to various subjects, containing information and readable at a distance [1]. Being a small sticker or a special label in a plastic case, it allows, for example, to track the movement of goods, improving the supply management system, and even prevent theft. Such RFID tags have become widely used in the trade industry. Moreover, Kevin Ashton explaining the basic idea of his invention used the term "Internet of Things". He once suggested that every single thing, in the real physical world, in IoT would have a digital counterpart as its virtual representation.

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_1

Today, the area of application of RFID technology is becoming more widespread. This technology is widely used for the automation of industrial processes, especially where there is a complex production of cars, appliances (refrigerators and washing machines). Specific libraries, such as the Vatican Library, which has over two million copies of books in its stock, have implemented RFID to speed up inventory and search for books, automate their delivery, and help combat theft. Over 700 of the largest libraries in the world are using or implementing this technology [2, 3]. RFID tags are also included in new passports in many countries around the world. Such documents are called biometric, e-passports, which contain a chip with the same information as the printed version. Increasingly, this technology is “taking root” in medicine. For example, in maternity hospitals, RFID wristbands are used to identify the baby with the mother. In conventional hospitals, they are used to tracking the movement of patients who need ongoing supervision. A new concept of a wireless sensor network was introduced, which track and control objects by connecting the tracker to the heart rate monitor [4]. Today, these devices interact with the Global Positioning System (GPS) devices, smartphones, social networks, cloud computing, and big data analytics to support the modern concept of IoT.

The direction of IoT developed actively since the 2000s when the number of devices connected to the Internet rapidly increased. The massive amount of big data used on the IoT is a concern for its users’ privacy. The General Data Protection Regulation (GDPR) was developed and implemented, the primary purpose of which is the protection of users’ rights. In their work, Alexia Kounoudes and co-authors studied the problems of applying GDPR requirements in IoT. The authors conducted a systematic literary analysis to better examine the problem of user privacy [5].

When working with the IoT, the group of twenty (G20) Artificial Intelligence (AI) Guidelines of the Organization for Economic Cooperation and Development and the General Principles for Human G20, and the Coordination Plan and Ethical Recommendations on AI Reliability developed by the European Commission, should be taken into account too. In particular, five interrelated principles should adhere to human-centered values and justice; sustainable development and prosperity; transparency and clarity; reliability, protection, and security; responsibility [6–8].

IoT requires a dedicated environment for uninterrupted, and therefore quality, work that includes directly different “smart” devices equipped with sensors, network access, and information transfer, and platforms for managing the network, devices, and applications. In the absence of at least one of these components, this system will not work. In order to fully harness the potential of the IoT, close cooperation is needed between businesses, mobile and Internet operators, governments, and even ordinary users.

This chapter aims to examine the basis of IoT in the health system, highlighting applying IoT technologies for the newly evolving personalized health. It discusses the latest and sophisticated IoT-derived techniques and popular examples of health. Moreover, this study focuses on the technical, ethical, and financial constraints in developing a better medical system that can early discover and diagnose illnesses. Healthcare providers could make good use of such innovative health systems, supplying the right data about the right patients at the right time and consequently, promptly and efficiently managing medical conditions. In this chapter, we discuss the role and some applications of IoT technologies in health and then show some selected medical cases highlighting an IoT-driven healthcare system followed by the prospective challenges of applying it in the health sector.

2 IoT and Healthcare

Healthcare is one of the noblest areas of IoT application. Through IoT, doctors can help people through the Internet. Portable IoT-based health monitoring devices can significantly reduce the distance between the patient and the doctor. IoT allows you to approach each patient individually, analyze their health status, and calculate their individual treatment method. With portable sensors, doctors can remotely monitor patients' health and respond in real time. However, real-time metrics require an uninterrupted Internet connection. Although IoT in healthcare is developing quickly, still not in full use in some medical industries [9]. The development of adequate Internet applications for traditional medicine still has some difficulties. With a significant increase in the number of medical research, the IoT will probably lead to attracting more of them in the coming years.

Modern medical professionals are faced with the need for collecting a large amount of big data and their analysis and interpretation to make informed and personalized decisions. All that takes considerable effort and time. New technologies of the IoT can speed up and facilitate this process. In connection with the mass introduction of electronic registration of health, a growing amount of digitized medical data is seen. Fully viewing and assessment of all this information takes a lot of time. Furthermore, training the medical staff of the technology based on AI, that is very associated with the IoT, is needed as well [10].

Through coordinated actions of such digital technologies as the IoT and AI, doctors can better tailor treatment to patients' needs. With these technologies, it is possible to handle a much greater volume of information to store and analyze it in order to closely follow the progress of a particular disease or process. Skillfully combining practical personal experience with the possibilities of new methods of diagnosis, collection, and analysis will lead to positive changes in healthcare management [11]. Figure 1 introduces the concept of IoT in healthcare.

Eventually, the IoT introduces network-enabled technologies, involving wearable and portable devices that can trigger, detect, synergize, and connect with other comparable media across the Internet. The IoT is deeply reshaping data production, use, and distribution. Average subjects frequently use these systems to follow their diet consumption, sleep, vital signs, exercise, and other physical states, whereas IoT technologies periodically gather and work on ecological data, which affects an individual's health. Eventually, this interoperability has introduced a start for novel production of medical alternatives.

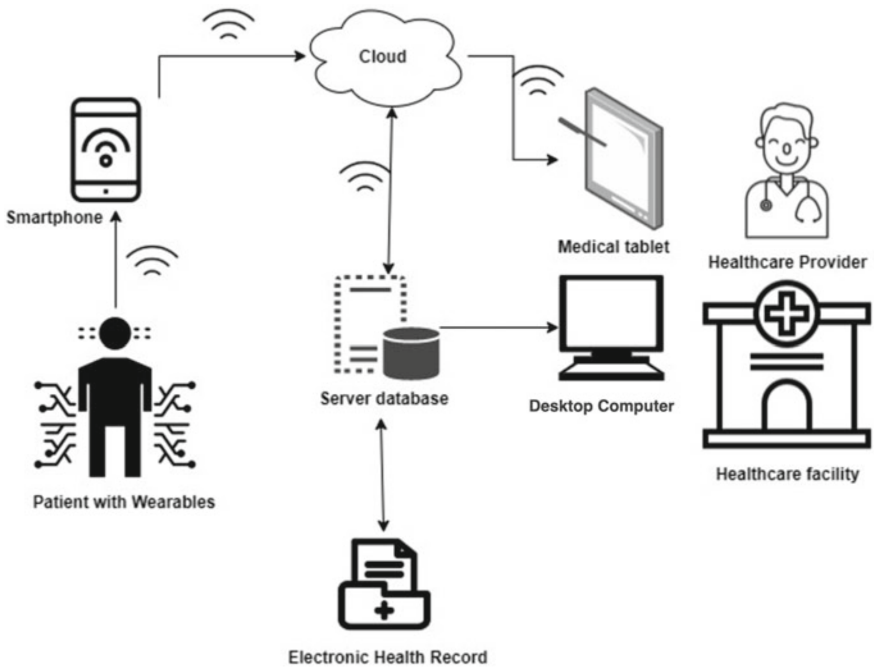

Fig. 1 The concept of IoT in healthcare

3 Applications of IoT in Healthcare

IoT in healthcare can have a substantial contribution to research, clinical practice, and patients management. In a broader sense, it also has various applications related to the insurance and industrial sector [12–15]. In all the aforementioned contexts, the contribution of IoT is based on four principles. The first principle is the collection of data, which is supported by interconnected devices such as sensors, monitors, detectors, equators, and cameras. The second principle is data conversion. This stated, it is imperative to mention that the input of sensors and other related devices is in analog form and it should become digital to undergo further processing. The third principle comprises data storage, which in most cases is achieved by a cloud-based system. The fourth principle is data processing through advanced analytics modalities, which eventually provides the users with information necessary for decision-making [15–17]. The aforementioned principles already exist in most aspects of healthcare, from hand-written patient records to interconnected laboratories' databases. What makes them unique in the IoT context is the fact that the flow of data is continuous, and the impact of IoT-based decisions can be instant.

With patients, IoT infrastructure consists mostly of wearable devices. Wearables may include oxygen saturation, blood pressure, pulse/heart rate, glucose level monitors depending on the history of the patient, and the parameters that should be monitored. These devices can ensure personalized attention in case of an acute condition or a gradual deterioration. They can also work as reminders if connected to physical exercise and calorie count software or appointment and referrals systems [13, 18, 19].

As far as physicians are concerned, IoT offers a real-time connection to their patients, to their colleagues, to their clinic or laboratory. A cardiologist can be notified about an arrhythmia affecting one of his patients, and a diabetologist can be informed about hypoglycaemia threatening one of his patients. In both cases, patients can have immediate medical guidance and support. Physicians can assess patients' adherence. It is not only a matter of outcome (e.g., blood pressure) increase in case patients neglect their treatment—it can also be a matter of device monitoring. This stated, pillboxes could be monitored counting how many times they were opened on a daily basis. Evidence suggests that IoT devices' datasets can assist physicians to identify the best treatment process and management strategy for their patients. This is a meaningful contribution to personalized healthcare. These big data on a larger scale could be the base of future treatment to outcome studies [20, 21].

Larger-scale Hospitals and Research Centers work as an incubator for IoT applications. This happens because of the great load and variability of data that need to be processed there, the responsibility these institutions bear as well as because of the funding they receive. In addition, to monitoring inpatients' and outpatients' health which has been previously addressed, hospitals and laboratories can use IoT to safeguard equipment such as wheelchairs, defibrillators, nebulizers, and oxygen pumps. Moreover, research facilities can monitor the course of experimental work, the deployment of equipment, and the availability of resources in a constant and time-consuming manner [22, 23]. Eventually, communication and sensor devices are growing into multidimensional information technology solutions in several instances. The growing IoT techniques have aided researchers and clinicians to structure novel healthcare solutions. The IoT-related health research is profound for its vital significance, involving effective prophylactic care and services at an elevated quality and less cost. The IoT is steadily securing basis as a novel research subject in several business and scholarly sectors, particularly in medicine. Impressively, for the dramatic dissemination of smartphones and wearable devices, the IoT-derived techniques are shifting health from a traditional hub-centered system to further personalized healthcare systems.

Recently, e-health is being used to provide individualized medical services to meet people's healthcare demands. IoT is profound progress in the era of big data that endorses several timely technical software to optimize services. Nowadays, the medical system is using IoT data analytics as a consumer data source to find more data, determine diseases early, and decide upon vital conditions for better life quality. Eventually, the swiftly expanding demand for the timely improved health system. IoT gadgets' can accumulate and distribute data instantly with other platforms on the cloud, facilitating a vast quantity of data to be collected, warehoused, and examined. The IoT devices would be functional in computerizing business or distant tracking

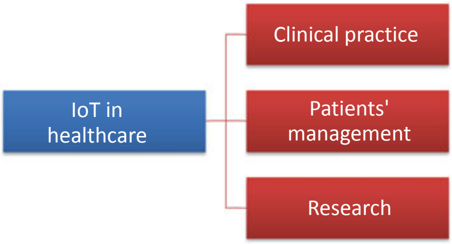

Fig. 2 Key applications of IoT in health care

of the local surroundings. IoT applications in health are promising for their ability to enhance access to care, reduce cost, and crucially boosting patients' quality of life.

Healthcare industry, as well as insurance systems, can also enhance their work through IoT applications. Data storage, product evaluation, patients' evaluation, and faster compensation services could be based on IoT. Figure 2 shows the key area of applying IoT in health care. However, such applications can face considerable legal obstacles because of data protection policy and because of the interference of financial interests in handling such information as well [13, 24].

4 Selected Cases of Using IoT in Healthcare

Now, mobile applications and wearable devices provide monitoring symptoms, medical education, fitness, and cooperative managing of illnesses and coherent care. Analytics software applications could increase interpreting data significantly and minimize the needed time to reassemble the produced data. Perspectives from studying big data would lead to the electronic evolution in the medical discipline, business procedures, and time deciding. Since the worldwide aging population rises, it would be vital to raising understanding and interpreting of data about health and well-being, minimize chronic and diet-derived diseases, and enhance mental abilities, boost mental health and lifestyles. Although it is impossible to list all the IoT healthcare applications, we will provide an overview of the renowned ones. Going through the scientific literature as well as some commercial resources, it becomes obvious that IoT is expected to play soon a prominent role in cancer care, patient-driven self-assessment procedures, drug delivery and adherence monitoring, exaggerations of acute conditions management and mental health.

Cancer care (CC) wearables have already been tested in clinical practice. In 2018, a Randomized Clinical Trial was presented in the Annual Meeting of the American Society of Clinical Oncology. The study focused on patients with head and neck cancer who were monitored via a Bluetooth-enabled weight scale and blood pressure cuff, together with a symptom-tracking app that was sending regular and emergency updates to patients' physicians. About 400 patients were involved in the study, and the patients who used this IoT-based system experienced milder symptoms in comparison with the control group, which was assessed physically on a weekly basis [20, 21, 25].

Diabetes is a model disease for assessing self-monitoring and adherence to treatment in various contexts including oral pharmacotherapy, injected insulin, blood glucose measurement, and blood pressure monitoring among others. IoT-based continuous glucose monitoring can be implemented on a wealth of existing devices. Although continuous monitoring and immediate intervention are mostly needed by type 1 Diabetes Mellitus (T1D) patients, accumulating evidence suggests that more punctual or even constant monitoring could prevent complications in patients with T2D [26, 27]. Smart insulin pens are relevant tools to assess the treatment adherence of patients with Diabetes Mellitus (DM). Although the existing devices focus on insulin injections, similar devices could also be used for pillboxes. Nowadays, such wearables are connected with smartphone apps and assessed by physicians regularly. Incorporating these modalities in an IoT context, physicians could be notified for patients neglecting treatment sooner and act accordingly [28, 29]. Closed-loop (automated) insulin administration systems have been long-awaited in T1D care. Potential regulatory and management flaws have hindered the introduction of such devices in clinical practice. Several advocacy activities from physicians and patients networks have already been observed taking into account that IoT can contribute significantly to tackling such obstacles. Although several steps need to be taken, an automated and IoT secured closed-loop system can be very important with regard to T1D patients who are at risk of diabetic ketoacidosis [30, 31].

Rather than DM, asthma is a chronic condition with a pattern of exaggerations that offers a fertile field for IoT-based healthcare. It represents a significant burden for hundreds of millions of people all over the globe. The majority of the patients are young and active seeking a stable quality of life. IoT wearables assessing saturation or warning about the presence of common allergens are important in the early detection and management of an upcoming exacerbation. In the same frame, IoT-based inhalers could provide the patients' physicians with reliable information about the adherence and the ability of the patient to handle the device properly [14, 32].

Asthma has a chronic aspect, of course, and so do mental health disorders. Apart from the aforementioned monitoring options, IoT can enhance patient support services. In combination with AI modalities, IoT can provide supportive chatbots for a wide variety of purposes from suicidal thoughts' detection to regular cognitive rehabilitation treatment in patients with dementia or mild cognitive impairment [16].

In this section, we have presented selected cases of IoT implementation in healthcare such as cancer care, patient-driven self-assessment procedures, drug delivery and adherence monitoring, asthma exaggerations management, and supportive care of degenerative mental health conditions as shown in Fig. 3. Such modalities state the potential of IoT in transforming clinical practice, patient management, and research if further and hopefully adopted.

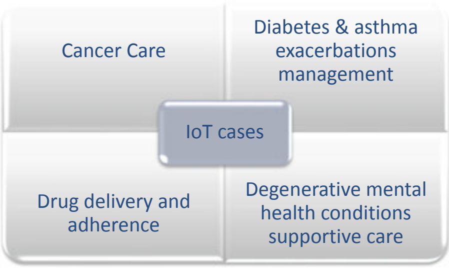

Fig. 3 Selected cases of IoT implementation in healthcare

5 Challenges of IoT in Healthcare

IoT is expected to bring a revolution in healthcare. However, there is no revolution without strife and conflicts. In fact, it is the conflict in the technical and moral level that shapes the way innovation is incorporated. The challenges of IoT in health care can be classified as technical, cost-related, and ethical as shown in Fig. 4 [28, 33, 34].

5.1 *Technical Challenges*

Technical considerations arise from the fact that IoT is still not a part of everyday life. In most countries, the fifth-generation wireless technology (5G) and subsequently IoT services are not available. Not only patients but also the vast majority of healthcare practitioners and researchers are not well acquainted with what IoT comprises and what can IoT do in everyday life let away from health care. This stated 5G can be considered as the first technical challenge that IoT implementation in healthcare faces [21, 35]. Implementing 5G requires the installment of multiple antennas, which is costly, time-consuming, and has been associated with a health hazard. Although there is not sufficient evidence for this claim, further research out to be conducted to establish the safety of large-scale use of 5G technology. Tackling the international repercussions of 5G, persuading the policymakers and changing (with their help) the public opinion can consume equal or even more time than safety studies. The prospective benefits from the use of IoT in healthcare can be an important argument in favor of 5G installment [16, 23].

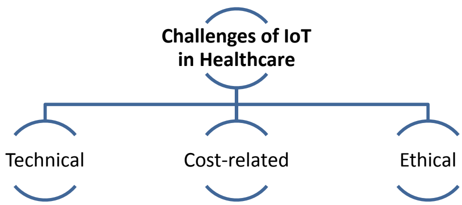

Fig. 4 IoT in healthcare challenges

The next technical challenge lies with the integration of data. Multiple sources of data mean multiple devices. In the healthcare sector, there is a variety of wearables and data collecting devices that cannot be easily modified to a unified pattern of data collection for technical and financial reasons. Even now, manufacturers have not achieved a consensus with regard to communication protocols and standards [21, 36]. Patients with the same disease can use different wearables addressing the disease itself or the vital signs of the person in general. Patients with diabetes, for example, may use different glucose and vital signs monitoring systems as well as a different closed-loop insulin pump. Altogether, this accounts for at least three different sorts of data from the very same patient. Even though these data will eventually be processed, this will require more time that can be a problem when it comes to acute conditions management, and it is also been a problem when multiplied by a vast number of individuals [13, 37].

5.2 Financial Challenges

As far as the financial aspects of the topic are concerned, we intend to elaborate on prospective cost-efficacy challenges. From a financial point of view, IoT belongs to the sphere of remote health applications. According to the International Data Corporation (IDC), the current budget for remote health monitoring in Europe is €10.41 billion, and it grew to over €12.4 billion. Such a budget might appear favorable with regard to the establishment of IoT health care. However, the complexities of implementing IoT have already discouraged many prospective investors. Sources of financial instability include the involvement of third-party service providers to ensure the quality of IoT and the associated connectivity infrastructure. Empirical observations suggest that both state and private healthcare providers would be unwilling to fund the establishment of an IoT healthcare network without evidence and experience from other healthcare systems/countries [38, 39]. To be more precise, the IoT healthcare market size was estimated to worth $60 billion back in 2014. It is expected to have reached a net worth value of $136 billion by 2021 [40]. It is noteworthy that the Compound Annual Growth Rate (CAGR) of IoT in healthcare is expected to reach or even exceed 12.5% over the forecast period. Whether this upwards shift will be sustained depends on the capacity of outsourced providers and healthcare providers to reach and maintain an adequate level of understanding and cooperation [41].

If implemented, IoT has the potential to reduce the financial burden of healthcare. Healthcare-related costs are traditionally divided into direct and indirect costs. The former account for expenses of healthcare providers, whereas the latter consists of expenses of the healthcare recipients including absence from professional activity, uncompensated treatment costs, and engagement of family members or other carers in their treatment. Given that IoT healthcare services have not been deployed in any major healthcare system yet, there is scarce evidence concerning its cost-effectiveness

[12, 42]. Economists have already highlighted aspects of IoT leading to a cost-effective model of development in healthcare. Proactive asset management, inventory management, strict quality control, product packaging optimization, and supply chain management have been recognized as prerequisites of IoT financial success in health care. However, to date, these concepts seem industry rather than health care-centered. Their adaptation to clinical practice will require close collaboration and deep understanding between economists, healthcare managers, and clinicians [15, 16].

5.3 Ethical Challenges

The ethical controversy of IoT in healthcare stems from the data management and care paradigm. The main debatable aspects, as far as the management of sensitive health-related data is concerned, are informational privacy, data sharing, and autonomy, data ownership, and consent, and unknown value issues. In the paradigm of care, the isolation and dehumanization of doctor–patient communication, the decontextualization of health and well-being, and the risk of non-professional care are alerting in terms of ethics [36, 43].

Repercussions from the field of ethics may influence policymaking related to IoT in healthcare. Any relative legislation should inherently abide by universal and regional standards such as the Universal Declaration of Human Rights and the General Data Protection Regulation (GDPR) in the EU, respectively. In this frame, it is also expecting that policymaking is a potential source of ethical obstacles to the implementation of IoT in health care [18]. Although the GDPR applies solely to the European Union, it can considerably influence IoT in healthcare-related research.

Examining some real-life scenarios in an IoT for healthcare context is essential to understand the ethical burden. Sensors following individuals in work and home will become a part of everyday life and may even be forgotten by their users. However, the same sensors fading in the background will monitor any moment of their users' personal life, including the normal deviations of pulse in a fight or in a happy occasion. Sound detecting and analyzing sensors may also "overhear" private conversations of the user. Even if the users consent to this for the sake of their well-being, this monitoring may violate the privacy of their family members, friends, and colleagues [12, 28].

Researchers have already come up with solutions promising a selective memory of IoT connected sensors. To our knowledge, drawing red lines between what is personal and confidential and what is clinically important is quite a difficult task. Everyday fights in family level or silenced conversations regarding debatable actions of the user may hide signs of occult hypertension or arrhythmia. Having a trained clinician or data scientist to discern what is important in case the sensors cannot achieve a selection consists a violation of privacy per se [14, 44].

At the same time, relying on data collected alone and selected by sensors to reach potentially risky decisions bears a considerable ethical burden [45]. What if an increase in anticoagulation dosage led by an IoT-mediated monitoring system results in extensive gastrointestinal bleeding? It could be argued that studying the use of sensors will provide the necessary evidence-based guidelines. Nonetheless, this cannot put in jeopardy the well-being and the life of patients who would not endure this risk otherwise.

Cybersecurity is an aspect of IoT healthcare services that ought not to be neglected as well. Data storage and procession requires cloud-mediated services [36]. Even if all the ethical considerations related to the healthcare and outsource services that will have access to these data are resolved, hacking remains a considerable hazard. Insurance companies, HR departments leading to unequal treatment of potential employees, can violate biometric data as well as medical history. In the same context, any other entity or individual could pose monetary or other claims in order not to decipher sensible information [35, 46].

6 Discussion

IoT technology helps to ensure the adoption and implementation of decisions in proper time based on the collection and processing of an enormous amount of data. Moreover, to handle such enormous amounts of information, which is dynamically changing, people have developed AI technology.

The process of a wide application of IoT is one of the fundamental benefits of the technological revolution. IoT will become among the largest innovations of humanity. The popularity of IoT is a response to the rapid growth in the past two centuries. It is known that making important decisions requires considering all the extensive amounts of information about several subjects and objects tangent to the processes in respect of which a decision is made. Basically, the decision should be taken in a mode as close to real time. Because of certain physiological and cognitive limitations, people are not always able in such circumstances to make quick and informed decisions. Consequently, IoT and AI technologies are relevant. The rational use of these technologies can bring many benefits to the medical sector.

The modern healthcare industry is a field where IoT becomes more prevalent. IoT directly affects people's lives and shows the importance of medicine as a sphere of activity in modern society. The medical systems are one of the most promising key areas that consume large numeric data. The significant flow of information and its transformation to a specific end product and its consumption is impossible using interactive information and innovative technologies. According to scientific studies, most of the leaders of the health sector believe that IoT will lead to a revolution in medicine in the next few years. This will involve mainly the following three areas: remote health monitoring of patients, prevention of exacerbations of chronic diseases, and the collection of information.

Health is the fastest-growing segment of the IoT. According to forecasts of scientists, the number of connected medical devices in the next 10 years will increase by 10 times. Several analytics predict that the number of individual wearable sensors for medical direction in the next two years will rise to 92.1 million units. In 2016, their number was only 2.4 million. At the same time, a variety of devices and smart systems are not intended to substitute doctors and nurses, it facilitates and optimizes their work. Doctors can help people remotely using Internet technologies, which is especially important in the period of deterioration of the epidemiological regime. Therefore, IoT allows finding the approach to each patient separately, to perform the condition of his health and calculate individual treatment.

Furthermore, IoT can facilitate the practice in medical care because of: automation of data collection in medical institutions, optimization of medical personnel, providing more accurate diagnosis of diseases, monitoring the patient's condition and course of the disease in real time, respectively. In addition, IoT can improve the effectiveness of prediction and prevention of diseases. It is possible that with a reasonable and coherent application of AI and the IoT, the number of errors in medical practice needs to be significantly reduced, which will help save more patients.

The emergence and widespread use of AI in various spheres of human activities have caused in this time many debates. There are certain barriers and risks to the technology development of IoT. The main systemic barriers include a lack of understanding of the values of IoT. Therefore, there is an absence or imperfect state of its development strategy. Also, significant barriers and risks include political; technological; legal regulation; education and motivation; financial and economic; security; privacy; compatibility of technologies and standardization. These barriers require further investigation to determine the program of measures for overcoming them because they are the source of a range of threats during using IoT.

7 Conclusions

Modern technologies are swiftly getting valuable in the health domain, involving devices that routinely observe health biometrics or monitor timely health-related data. Using Internet technologies and the large accessibility to smartphones, healthcare providers and patients are using mobile apps to manage health. Combining IoT techniques with big data is crucial in such a health arena. In the healthcare field, IoT is revolutionizing the creation of effective healthcare delivery, creating a platform for communication between different health segments, providing digital support at every turn, and facilitating the rapid transformation of modern medicine to the demands of time. Healthcare providers could use such innovative health systems, supplying the right data about the right patients at the tight time. Consequently, a promptly and efficiently medical decision-making can be conducted. However, the emergence and widespread use of AI in various spheres of human activities have caused in this time many debates. There are certain barriers and risks to the technology development of IoT. The main systemic barriers include a lack of understanding of the values of IoT and, therefore, the absence or imperfect state of its development strategy. These barriers require further investigation to determine the program of measures for overcoming them. This chapter has provided innovative insights regarding the role and some applications of IoT technologies in health. It also showed selected medical cases highlighting an IoT-driven healthcare system and the prospective challenges of applying it in the health sector. Finally, more research on AI and IoT or in any way associated with the various aspects of their development, implementation, and use is encouraged as the way for future healthcare.

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IoT-Based Computational Frameworks in Disease Prediction and Healthcare Management: Strategies, Challenges, and Potential

Ritwik Patra, Manojit Bhattacharya, and Suprabhat Mukherjee

1 Introduction

The Internet of Things (IoT) is a trending topic of discussion and research in information technology (IT) sector and even healthcare industry, because of its ability to connect various sensors and devices to form a cloud database with all available information impacting on advancement and betterment of humanity through the Internet [1]. The Business Insider report states that by 2020, 34 billion IoT-based medical equipment will be connected to the web network to create, process, and exchange huge quantities of data between web and IoT-based medical devices [2]. Internet assistive disease prediction is the development of advanced technology supported on a web-based system for the evolutionary development and betterment of electronic devices, servers, software applications into next-generation know-how practices for upbringing the medical and healthcare industry [3]. Internet technology provides a broad spectrum for better health care and clinical facility with safe and secure private data, cost-effective, time-saving, and easy to handle. The use of a server-based or cloud computing system for the generation and storage of medical and health data provides fast and easy assistance to the healthcare provider to better assist and health monitoring. Health monitoring systems include the processing and analysis of data collected from smartphones, smartwatches, smart bracelets (i.e.,

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_2

wristbands), and various connected devices. These sensors are essential for the diagnosis and management of patients with chronic diseases (such as hypertension and diabetes) or the surveillance and assistance of older people.

The application of the Internet in healthcare management shows a wide range of functions including:

- Rapid monitoring and diagnosis of chronic diseases with continuous health observing.
- Development of electronic health and medical records with all patients' health data and diagnostic medical information, assisting the healthcare worker for fast analysis and treatment procedure.
- Use of cloud-based servers to store the available information connected with Internet servers and medical devices.
- Clinical trial monitoring and also therapeutic drug monitoring.
- Use of sensors-based technology and devices for collecting raw health data and deals with chronic diseases like diabetes, heart disease, and cancers.
- Development of mobile health and telehealth along with various mobile phone applications used by the patients themselves for tracking their disease.

The objective of this chapter is to discuss the various strategic development and computational framework associated with the IoT-based healthcare system that is used for disease prediction, healthcare assistance, and management, based on the finding from the recently published research paper or review paper. The use of electronic health records including both cloud-based and server-based software enhances the quality and quantity of health monitoring and fastens treatment procedures. The cloud computing system is the key component of IoT-based healthcare system that collects the data, store it, process it, and analyze it to make it easily accessible. This chapter also coincides with the various remote health and mobile health technologies available for the advancement of the digital healthcare system. Furthermore, it emphasizes on the use of IoT-based techniques in combating the global pandemic of COVID-19. The advancement of the IoT-based computational framework in the healthcare system bring revolutionary changes in the advancement of the medical industries and help the healthcare providers for smooth and fasten healthcare management and health strategies. However, the limitation of data security and privacy is still a challenge for the IoT-based healthcare system and requires further future research and development.

2 Disease Prediction and Healthcare Network

Internet-assisted disease prediction is an advanced conceptuality of detection, monitoring, and fast treatment procedure based on software application and artificial intelligence trained model or electronic device for the development of next-generation healthcare advancement. Nowadays, the entire medical industry mostly based and interlinked with the uses of IoT and electronic web for the healthcare facilities. It can perform various functions such as monitoring patients health, patient's medical history analysis, digital trail monitoring, drug monitoring and also can be used for equipment and patient healthcare organization, smart patient's intake and occupancy, smart pill dispensers to monitor the patient's medicine intake and alert system.

Point of care (POC) diagnostic is used for bedside medical testing with immediate result enhances the faster treatment procedure and also help elderly, physically disabled, chronic diseases, and emergency patients [4]. For example, the use of field-programmable gate arrays (FPGA), digital signal processors (DSP), and graphics processors in ultrasound technology has reduced the size of traditional ultrasound scanners to a portable ultrasound scanner (PUS) in handheld level making easy to perform POC diagnosis, remote health care, and emergencies conditions [5, 6]. The shortage of expert sonographers could be overcome by the use of telesonography technology using high-efficiency video coding (HEVC) and H.264 encoding, where a non-expert performs POC ultrasound and is transmitted immediately to expert for diagnosis [7, 8].

Comarch Healthcare provides a wide range of healthcare solutions including IT software for hospitals, software products for radiology, remote medical care, and medical record management and expertise in IoT, artificial intelligence, cloud platform, m-Health, and cybersecurity for health care [9]. It also has been innovated various products including:

- ***Comarch Diagnostic Point***—It is the solution for a medical facility seeking to overcome the challenges, including appointment scheduling and availability, time management, and cost management. It consists of devices and software enabling quick and straightforward measurements of each patient's basic vital parameters that operate via an application available on a tablet to collect data from the peripheral device using Bluetooth and sent it to Remote Care Center [10].
- ***Comarch Life Wristband***—It is all time wearable waterproof devices with long battery life and an SOS button that enables patients to communicate and request help from the telehealth center. The sensors detect the loss of consciousness and automatically alert the telecare center. The build-in health care allows medical staff access to patients EHR and all personal and emergency data [11].
- ***Comarch CardioVest—***It is designed to perform precautionary examinations, diagnosis, and observation of adult cardio-patient. It records and transmits the ECG data to the telemedicine platform, which interprets the data and makes advance investigation about the situation and deviation from the standard [12].

The application of IoT in disease prediction and healthcare system is schematized in Fig. 1, including the use of sensor-based technology, m-health, and electronic medical records is used to obtain the primary health data of the patients that are stored in the cloud to access by the medical professional for the healthcare intervention and management.

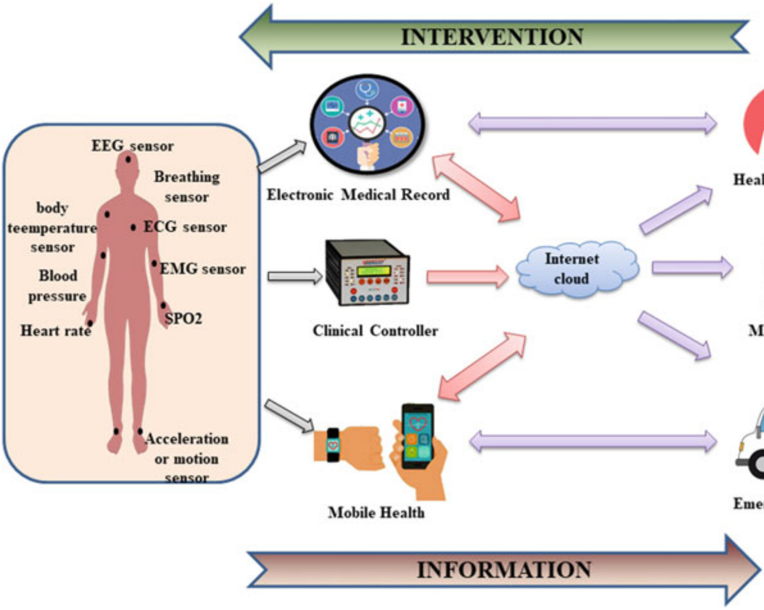

Fig. 1 Application of the Internet of things in the healthcare system

3 Medical History Analysis

The complete medical history and records are very much vital for the diagnosis of chronic disease patients, as they have to undergo multiple consultations. Electronic health record (EHR) is the real-time-based digital patient's health and medical report which can be instantly accessible to the authorized users securely. It may facilitate the availability of comprehensive information on patient health at the point of care delivery [13]. Electronic medical report (EMR) or EHR contains the patient's clinical history, diagnostics, prescriptions, treatment strategies, immunization dates, allergies, radiological images, and pathological data, providing evidence-based resources which are used by healthcare professionals to make patient care and management decisions and can also document for potential usage [14].

EMR software systems can monitor nearly all characteristics of a doctor's visit, follow all examinations, schedule appointments, and document the entire clinical findings in a way that makes it more readily available, eliminates misdiagnosis, and rapidly communicates vital details to doctors, including drug allergies, current medications, and more [15].

3.1 Cloud-Based EMR Software

The cloud-based software is easily accessible from anywhere and anytime with minimum hardware requirements, i.e., no need for maintains server or additional workstation. The data are stored in a secure cloud, thus no need for backup but has to pay monthly for use. The benefits of cloud-based EMR software are:

- It runs on a web platform, requiring no hardware or software installation preventing interruptions of cash flow and gets a faster return on investment.
- Service providers maintain all responsibility for security patches, code updates, and re-encryption.
- It contains drug libraries and intuitive decision-making tools that effectively determine and prevent medical errors.
- Highly flexible to use, can add new data and information doctors list anytime.

3.2 Server-Based EMR Software

Server-based EMR software provides on-site advantages with a greater up-front cost. It owns both software and license to install in many devices of user choice without any external support. It mainly relies on remote connection such that the user can access whenever they need. The advantages of server-based software are as follows:

- High-speed performance and support as it is an on-site system even without a dedicated Internet connection.
- The initial cost is higher due to an increase in hardware requirements and installation and for purchasing software licenses. But, over time, the expense can be less than the lease of SaaS licenses.
- It was secured by encryption of network firewalls and security controls.

The various types of cloud-based and server-based EMR software are listed in Table 1. The cloud-based software includes various packages like PrognoCIS, DrChrono, Kareo Clinical, NextGen Office, WebPT, Office Practicum, and many others. These solutions mainly serve as customized tailor-made electronic health record workflow to conveniently monitor the patient intake, appointments, patient care, clinical charting, billing, insurance, telehealth, outcome tracking, and healthcare management. Whereas the server-based software such as Athenahealth, eClinicalWorks, EpicCare, Allscripts, AdvancedMD, ChiroTouch Chiropractic provide web-based medical facilities for both healthcare and administrative management.

Table 1 List of various types of cloud-based and server-based EMR software and their functions

Cloud-based EMR software		Server-based EMR software	
Platform	Function	Platform	Function
PrognoCIS	Provides a customized and tailor-made EHR workflow to clinics and hospitals with rich and specialty-specific content. Virtual medical encounters are improved by Telemedicine	Athenahealth	Provides web-based medical facilities like patient booking, prescriptions, and also deals with practice management, care facilities, coordinatio
DrChrono	Patients' intake, medical charting, billing, and insurance management are done by healthcare personals and healthcare providers	eClinicalWorks	Provides both on-spot and virtual solutions to ambulatory practices, emergency care facilities, ACOs, hospitals, and lots of specialist choices
Kareo Clinical	Medical specialists can do patient scheduling, insurance confirmation, delinquent accounts management and the collections procedure, keeping patient records, developing customized reports, and more via	EpicCare	In large medical centers, hospitals, and practitioners give access to EMR and provide facilities to avail different specialists
NextGen Office (Formerly Known as MediTouch)	Generates eligibility for insurance, scheduling appointments, request refills, organized telehealth, and connects healthcare providers with patients directly	Cerner	Manages both clinical and administrative works as well as provides ambulatory practices or primary care facilities
WebPT	It allows therapists to generate and track patients' records, and transfer it via fax or a HIPAA-compliant portal. Manages patient appointments and reminders, medical record storage, and tracking	Allscripts	Helps to manage electronic health records (EHR), Financial issues, Medicinal chartings, and Population Health Management and also provides daily health planning, various specialist consultation

(continued)

Table 1 (continued)

Cloud-based EMR software		Server-based EMR software	
Platform	Function	Platform	Function
ECLIPSE Practice Management Software	Helps in case management by Single Doctor via "Real-Time Data Flow." Also gives access for billing, insurance claims, appointment management and reminder, and document management	Amazing Charts	Helps small practitioners and patients with bookings, billings, web-based health reports
Office Practicum	Allows to schedule appointments, managing clinical reports, testing, billing. Also plays a major role in pediatric treatments	AdvancedMD	Manages independent practices, EHR, telemedicine, relationship with patient, business analytics reports, and physician-performance rating
Genesis Chiropractic	Offers EHR, appointments, data recording, billing within a single integrated web-based system	Greenway Health	Helps to manage EHR, revenue cycle, patient care, and coordination.
The Valant Behavioral Health	Provides tools for scheduling appointments, managing clinical reports, testing, billing. Increases the efficiency in medical services by managing data, relation with patients via the patient portal	Chartlogic	Gives an ambulatory electronic health record system along with appointment, patient relations, charting, e-prescribing, E/M coding functionality
Modernizing Medicine's EHR & Healthcare IT Suite	Manages several healthcare specialists and facilities under the same umbrella and improves healthcare services	ChiroTouch Chiropractic	Facilitate both small and medium-sized practices with appointments, specialist suggestions, billing

4 Cloud Computing System

The cloud computing system is the technique of storage and analysis of large-scale data for the development of IoT-based healthcare model and database. It stores information in a network of several servers and has the adaptability of the equipment and the capacity to manage such extensive data and complex calculations and can provide continuous rich quality data in a short period of measurement [16]. Cloud providing companies uses substantial server farms and can categorize into three types: software-as-a-service (SaaS), platform-as-a-service (PaaS), infrastructure-as-a-service (IaaS), and database-as-a-service (DaaS) where they distributed computing and data management to various server farms for fast and inexpensive methodology [17, 18]. IaaS model consists of virtual machines (VM) and storage area, used for keeping data and balances computational capacity for cloud computing, and can be accessed by a user to use the software and install as per their need [19]. PaaS controls the handiness and convenience of programming models via web such that the user can use the web applications without downloading or installation of software [18]. SaaS and DaaS service models provide its user to access software deployment and databases, respectively, without any software installation or hardware setup [17]. According to the report of 2017 by "Markets and Markets," the healthcare cloud computing industry is expected to grow at CAGR of 18% within 2023 including the growth of EHRs, picture archive communication systems (PACS), vendor-neutral archives (VNAs), SaaS, and IaaS [4]. The cloud computing system relies on the fog and edge computing layers and is shown in Fig. 2. The edge computing layer servers as the source for retrieving the primary data form smart devices, EMR, smart hospital server, body sensor and forward it to the fog layer via Bluetooth, WiFi, and Internet. The fog layer is the intermediate between the edge and the cloud system.

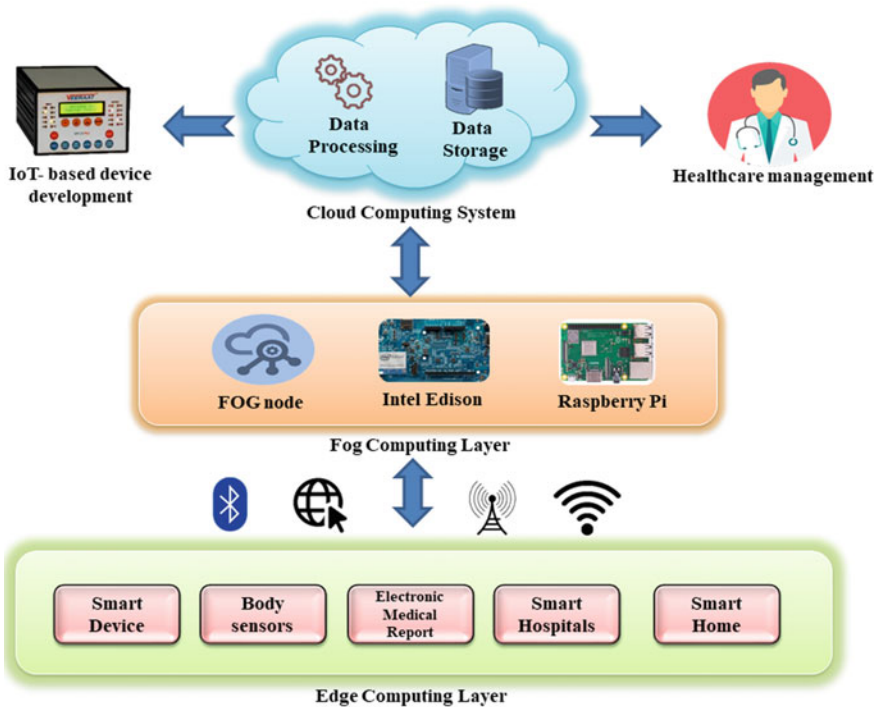

Fig. 2 Cloud computing system: frameworks and layer

4.1 Fog-Assisted Cloud Computing

Fog-assisted cloud computing system was based on the fog of things (FoT), where multiple fog nodes are connected for communication using IoT, finally, the stored data in the cloud for processing, enduring storage, and exploration [17]. Fog cloud computing is the connecting link between the cloud computing layer and the edge computing layer by enhancing the efficiency and reducing the latency to improve the quality of service [20]. It does not require computational resources, thus bringing closer to the user and reducing latencies as compared to remote cloud servers [21, 22]. Intel Edison and Raspberry Pi are fog devices that can act as a gateway between cloud and mobile clients. Intel Edison contains dual-core, dual-threaded 500 MHz Intel Atom CPU along with a 100 MHz Intel Quark microcontroller, having 1 Gb memory with 4 Gb flash storage, WIFI-enabled and used in Linux operating system. Raspberry Pi was made up of 900 MHz 32-bit quad-core ARM Cortex- A7 CPU with 1 GB RAM, WIFI connected through Realtek RTL8188CUS chipset dongle [23]. GeoFog4Health framework is employed with both Intel Edison and Raspberry Pi as a fog computing device having four different layers including cloud layer, fog layer, intermediate fog layer, and client-tier layer [17].

4.2 Edge-Assisted Cloud Computing

The edge-assisted cloud computing system relies on both data producers and consumers. It mainly consists of network edge and computer edge that reduces the latency, transmission power and also increases the analysis power [24]. The network edge nodes perform the computational tasks and service requests from the cloud, while the computer edge stores data, compute it, and translate the analysis form cloud to edge node [17]. It provides assistance to cloud backend and advantage over cloud processing in such a way that primary disease diagnosis at the edge and supervising at cloud [25]. Routers, bridges, wireless access points used as edge servers and the devices include smart devices and mobile phones working cooperatively to enhance the capability of edge computation [24].

5 Clinical Trial Monitoring

The International Council for Harmonization–Good Clinical Practice (ICH-GCP) is an international standard of ethical and scientific quality for the design, conduct, recording, and reporting of trials involving human subjects. The main purpose of ICH-GCP is to provide a unified standard for the mutual acceptance of the clinical data throughout the world. The recommendations have been established taking into account the existing good clinical practices of the European Union, Japan, the USA, as well as Australia, Canada, the Nordic countries and the World Health Organization (WHO), and they should observe when conducting clinical trials for human safety and well-being [26]. Clinical trial management software serves the task of overseeing all clinical trials, including patient records, scheduling, monitoring, analysis, and data processing.

5.1 Trial Oversight Committees

The experienced trial oversight committee is established for the security system of trail monitoring based on the mass and convolution of the trail. The trial management committee consists of the chief investigator, statistician, trial coordinator, nurse coordinator, and data manager that conduct and monitoring the path by ensuring that all protocols and standard procedures are being followed. The Trial Steering Committee supervises the trial and designs it error-free before the initiation. At the same time, the Data Monitoring Committee provides safety to trial, safeguard the credibility and validity of the study [27].

5.2 Central Monitoring

The central monitoring works in addition to the trial oversight committee for the assessment of correct entry procedures and protocol are being followed or not. It uses a statistical method for central monitoring that helps to identify the deviation from actual patterns, suggesting incorrect practices, data forgery, thus detecting target sites for further exploration [28]. It can perform the following functions:

- Range check for missing and invalid data.
- Calendar check for early indication of error.
- Test and compare data to identify trends, including digit selection, rounding, or irregular frequency distribution.
- Assessment of reporting rates and performance indicators, including the daily appointments schedule, the average length of visits, and delayed input or transmitting results.

5.3 Drug Monitoring

Drug monitoring is the method of clinically monitoring and analysis of the drug's concentration in the patient's blood circulation at a fixed, regular interval to maintain homogenous consistency and optimizing dosage regimens [29]. Therapeutic

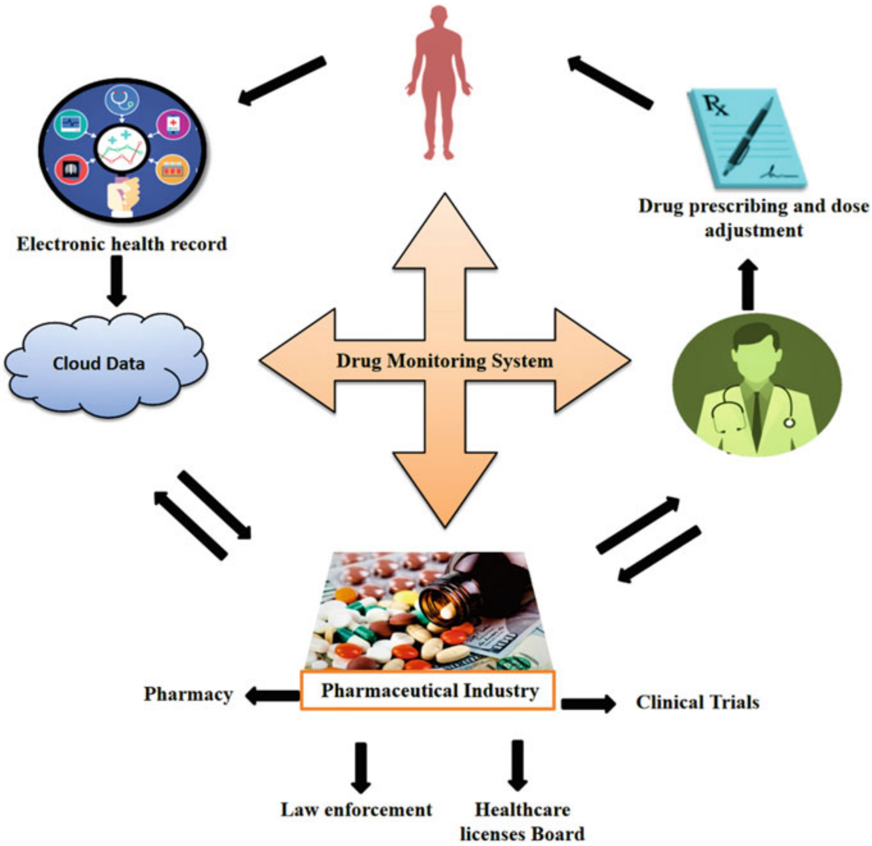

Fig. 3 Drug monitoring System

drug monitoring (TDM) is the combination of knowledge of combining knowledge of pharmaceutics, pharmacokinetics, and pharmacodynamics and is the clinical measurement of chemical parameters with proper medical interpretation for prescribing to patients safely [29, 30]. It monitors the drugs with low therapeutic ranges, pharmacokinetic variability, multiple concentration target, and causing adverse health effects based on the correlation between dose and concentration and its therapeutic effect. The system and workflow of the drug monitoring system are schematized in Fig. 3.

6 Sensor-Based Healthcare Monitoring

The sensor-based health monitoring system is focused on the information available on the health condition of the patient in the form of a digital signal, and it alerts the patient through an auditory warning [31]. Among the several types of sensors, ECG, temperature, pulse rate, and respiration sensors are widely used for continuously monitoring health. It is generally attached to the body of the patient or maybe embedded in the clothing, shoes, or watches [32]. The sensors can measure both physiological changes occurring within the body and the changes in the external environment using ambient sensors and are listed in Table 2.

Table 2 Different types of sensors used for healthcare management

Sensor type	Function in healthcare management
Accelerometer	Measure the acceleration of body movement. Record body posture and fall from bed
Humidity and temperature sensor	Contactless automatic continuous temperature monitor and control of both patient and environment
Sweat sensor	Use as a biomarker to provide information related to blood salt concentration, glucose, amino acids in the body. Used in wearable devices to monitor body fluids
Respiration sensor	Used as a visual sensor to monitor patients during MRI, surgery, also used to monitor diseases like sleep apnea or pulmonary diseases
Blood glucose sensor	Important diabetes monitoring for body glucose level. Used as a bio-implant device based on infrared, optical sensors, or ultrasound technologies
Blood pressure sensor	Continuous blood pressure monitoring. Used in wearable device
Electrocardiogram sensor	Measure the electrical impulse through heart muscles
Pulse-oximetry sensor	Uses a non-invasive system for assessing blood oxygen and hemoglobin. Attached to fingertip and now used in wearable device to measure SpO2
Sensor-enabled pills	Deals with chronic and complex disease. Ingestible pills upon consumption give vital health status to a linked wearable device and also saved in computer cloud, further used by doctors to monitor patients, diagnosis and track their activities and suitable treatment plan
Sensor-enabled smart pill bottles	Alert and record for regular pill consumption integrated with cell phone or smart device. Upon missing dose sent alert to the healthcare provider
RFID sensor	Developed for medical management solution
Electroencephalogram (EEG) sensor	Analyses the brain commotion, tumors, dizziness, and sleep problems that have been developed to identify the driver’s sleepiness/anxiety management
Electromyogram (EMG) sensor	Analyze electromechanical muscle activity during contraction and relaxation to predict neuromuscular syndromes, assess back pain, and kinesiology

Tracking drugs, patients, and devices using various sensor-enabled systems become a practical and essential aspect in healthcare industries. The continuous tracking of patient health, medicine intake, and other activities of patients reduce the cost and time expenditure of healthcare providers for managing chronic disease. The sensors are now used in various wearable devices, smartwatch, fit-band, and even in smartphones with various healthcare monitoring features. The use of radio frequency identification (RFID) technology is used for health administration solutions and drug management to monitor the drug stock [32]. RFID-based smart intensive care unit (ICU) system is generated that collects medical data in a real-time order based on a three-layer sensor system for precious detection and management [33]. It consists of an antenna and an IC chip embedded along the tags containing the identification code to transfer the data upon electromagnetic field generation. The RFID-based healthcare monitoring system is very low-cost, low powered requiring minimal effort and control and can perform simple-to-execute observing and transmitting clinical data of patients [4]. WSN is an autonomous sensor capable of recording and transmitting environmental or physical data, in which each sensor is coordinated with a multi-system prototype to provide assessment and control functions [34].

7 Remote Healthcare System

Remote monitoring is the process of tracking the activities that are previously conducted on-site to increase the efficiency of analysis and speeding up time [35]. The remote patient monitoring system provides the service to the healthcare provider to access the patient's status through the use of a computer or Internet-based advanced technology. The benefits of remote healthcare monitoring are:

- Better access by physicians to increase the capacity of patient's treatment, for example, "The Care Innovations® Health Harmony platform" allows access to care for patients nationwide [36].
- It can improve the quality of care by directly connecting the patient's data with the clinician.
- It provides patient comfort and engagement and also an assurance for well-being.

The Remote Healthcare System Company provides technology solutions for design, analyze, and optimize the digital healthcare process [37]. The equipment is the interface between the human and medical device, ergonomically designed with customized parameters to facilitate functionality and development and are of following types:

- **RHS PRO**—Integrated diagnostic device with real-time clinical analyzes that protect patient health history and allow for review and medication certification.
- **RHS COMPACT**—It is a portable version of the diagnostic device with a real-time clinical review that maintains patient health history and allows for inspection and medication certification and prescriptions.

- **RHS CASE**—It is designed to be used in unusual situations or places with low geographical links. The container is stable, absorbent in shock, and transportable.
- **RHS LIGHT**—The station is designed for electromedical management and video correspondence.
- **RHS HOME**—The station is designed for electromedical management and video interaction.

CareNet is an integrated wireless sensor networking environment for remote health care, built upon a multi-layered software infrastructure having application-level routing, multi-hop packet forwarding where the data streams will be forwarded simultaneously through different threads in the system and also a mobile sensor hand-off for ensuring the reliable packet delivery and remove the duplicate data packets. It has high reliability, good scalability, extensibility, and performance, integrated into a web-based patient portal with confidentiality and privacy [38].

8 Mobile Health (M-Health)

The WHO's Global Observatory for eHealth defined Mobile health (m-health) as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices." On broad aspects, it is referred to as the use of a mobile device to collect the real-time medical data from users that are stored in the online server or cloud for access by the doctors, hospitals, insurance providers, and everyone associated with healthcare management. The application of cell phones includes the use of voice message and short messaging service (SMS), general packet radio service (GPRS), third and fourth generation mobile telecommunications (3G or 4G), a global positioning system (GPS), and Bluetooth. In a worldwide survey on m-health done by WHO on 2009, it was found that the m-health initiative is mainly categorized were health call centers/healthcare telephone helplines (59%), emergency toll-free telephone services (55%), emergencies (54%), and mobile telemedicine (49%) [39]. The application of m-health in health care includes education and awareness, disease diagnosis, outbreak tracking, remote data collection, remote monitoring, personal digital assistance, telehealth or telemedicine, and even help in disease management [40]. The use of a smartphone application or Web site is the best way for delivering m-health to a wide range of peoples as it is easily accessible, not require much knowledge, and also meager cost. The m-health applications market is expected to witness significant growth due to high consumer demand to monitor their health. It helps by reducing the cost of appointments, medication reminders, and recovery instructions. According to a report published by "Fortune Business Insights," the Global m-health applications market was $11.17 billion value in 2018 will grow at 21.1% CAGR and by the end of 2026, it will reach to $57.57 billion [41]. The various m-health applications are listed in Table 3.

Table 3 Types of m-health applications and their functions

m-health applications	Description and functions
AirStrip, AirStripOB/Cardiology	Maintain synchronization among multiple devices. Data from several EHR, many clinical solutions accessed through smartphones, tablets, and computers from hospitals, post-acute, and community-based care organizations to monitor cardiac conditions
Aetna, ITriage	Direct accession to health information and sequential treatment guidelines for patients' health issues in a convenient and effective procedure. It directs the patient on treatment procedures, health insurance schemes
Cerner, CareAware Connect	Manage multiple clinical communications on a single platform. Users can get medication information related to health issues
DSS Inc.	Provides clinical care facilities with reduced administrative costs, and designated for mobile screening tool
Epic Systems, MyChart Mobile	Helps to access data related to test reports, immunizations, medication, and health conditions from previous in-office visits of patients. Also allows to take appointments, healthcare bill payments, uploads fitness data given by patient from wearable health device
GetWellNetwork, Marbella	Accessibility to patients' data and collection by healthcare providers, hospitals, and other associated service providers through mobile devices. Integration with other vendors allows instantaneous alerts and tracking to alleviate manual follow-ups
MEDITECH, Ambulatory EHR	Helps to avail complete web charts of patients including test reports, prescriptions, appointments, progress in health condition by tapping their name. Also help identify at-risk patients by population management tools
PatientKeeper	Allows healthcare workers to order radiologists' equipments, medical personals, and similar services for their patients across all hospital departments to keep track of allergies, test results, patient vitals, and related health data as a way to achieve accuracy and to save time
PatientSafe, PatientTouch System	Helps to maintain communication within the healthcare authorities and bring them under a single umbrella to improve care efficiency
Spok, Spok Mobile	Helps to coordinate clinical care units to improve care efficiency. Integrates with current EHR systems for care responsibilities and hospital-wide scheduling via preferred devices like smartphones or smartwatches
National Health Portal India	Government of India official application with intuitive UI, which is simple, easily accessible, and provides health information to rural illiterate or semi-literate peoples
AIIMS-WHO CC ENBC	Provides assistance and help to nursing colleagues and neonatologist across small hospitals with limited resources
HealthyYou Card	Search engine and online appointment booking with alerts and reminders

(continued)

Table 3 (continued)

m-health applications	Description and functions
1mg	Online pharmacy supplying prescription medicines and OTC, along with online doctor's consultation

8.1 Telehealth and Telemedicine

The Health Resources Services Administration defines telehealth as "the use of electronic information and telecommunications technologies to support long-distance clinical health care, patient and professional health-related education, public health and health administration." The various tools include Internet accession, live streaming, storage and forward imaging, streaming media, and wireless and terrestrial communications [42].

Napier Health care provides a leverage telehealth solution to connect with patients virtually. Napier Remote Patient Management is a unified web-based platform that enables the health-workers to remotely monitoring the patient's data collected via a mobile application to manage the health condition. It is beneficial to the health-worker by allowing continuous monitoring of health indicators, clinical interventions, stratifying patients according to health conditions, and reducing paper works and management. The patients also benefitted by easy accessibility to personal data, video consultation with doctors, and increase adherence to treatment plans [43].

WHO defined telemedicine as "The delivery of healthcare services, where distance is a critical factor, by all healthcare professionals using information and communication technologies for the exchange of valid information for the diagnosis, treatment, and prevention of disease and injuries, research and evaluation, and for the continuing education of healthcare providers, all in the interests of advancing the health of individuals and their communities" [44]. Smartphones are now the fastest-growing market with a massive number of users and easily accessible. Consequently, the use of a mobile application for telemedicine is very much accessible and beneficial to both the user and the service provider. MDLIVE is a mobile application that connects with medical and pediatric physicians, as well as accessing behavioral and psychiatric health services. It is fast, simple, and convenient to consult with a state-licensed and board-certified physician for a non-emergency situation with waiting times of less than 15 min.

9 Internet-Assisted Healthcare Management for the Global Pandemic of COVID-19

The coronavirus disease or COVID-19 is a worldwide pandemic caused due to Severe Acute Respiratory syndrome coronavirus-2 (SARS-CoV-2), affecting more than 215 countries worldwide with 6,057,853 confirmed cases and a death toll of more than

371,166 on June 1, 2020, as reported by the World Health Organisation (WHO) in situation report 133 [45]. The first outbreak occurs in late December 2019 at the Wuhan seafood market of the Hubei province of China, and later on January 9, 2020, it is officially declared as a pandemic by the WHO [46]. Symptoms can occur 2–14 days after virus exposure including fever or chills, cough, shortness of breath or breathing difficulties, exhaustion, muscle or muscle aches, headache, loss of taste or scent, sore throat, coughing or runny nose, nausea and vomiting, and even diarrhoea. The lack of proper therapeutic drugs or vaccines created a worldwide loss of lives as well economy.

9.1 Disease Prediction and Diagnosis

Reverse Transcription-PCR (RT-PCR) is the first test for the detection and confirmation of COVID-19, but in these fast-spreading pandemic, it is not enough to counteract the emergency condition. The use of IoT, machine learning, artificial intelligence (AI) can help in overcoming the problem [47]. The Internet-assisted AI-algorithm-based automated radiology techniques like computed tomography (CT) scan, magnetic resonance imaging (MRI), and digital X-rays are used for fast diagnosis and detection. The use of deep convolutional neural network (CNN) is used to pre-train the model of ResNet50, InceptionV3, and Inception-ResNetV2 for the prediction of COVID-19 based on analysis of X-ray dataset with high accuracy [48]. The use of IoT and AI for the development of COVID-19 Intelligent Diagnosis and Treatment Assistant Program (nCapp) for providing clinical assistance based on GPU-based cloud computing system and EHR used for analysis, detection, diagnosis, and stratification of patients according to the health by the top medical advisors [49].

9.2 Healthcare Management

The situation of nationwide lockdown and home quarantine throughout various countries of the world created health mismanagement that can be overcome by m-health, and some of them are listed in Table 4. The m-health industry changed to perform the following functions:

- Medical Distancing- telehealth and telemedicine implements the contactless healthcare facility and lowering COVID-19 transmission.
- Crowdsourced disease monitoring- timely tracking and monitoring the infection, digital health experts keep surveillance on patients health data and travel history.
- Health Information Exchange to boost interoperability-development of healthcare infrastructure based on patients medical data, diagnosis, and treatment for worldwide circulation for better health management.

Table 4 Use of various m-health applications and web server for the COVID-19 pandemic

m-health for COVID-19	Developer country	Description and function
Desescalapp	Spain	All updated and simplified official information on COVID-19 de-escalation is given step by step
Smittestopp (digital contact tracing)	Norway	Accelerate the contact tracing process of a patient more rapidly and accurately. Helps to prevent more spread of COVID-19
Covidtracker	Switzerland	Tracks current and past symptoms by asking basic demographic information in Switzerland
Open coronavirus	International	A digital solution to monitor, diagnose, and contain SARS-CoV-2 infection for application of controlled quarantine measures to minimize the general quarantine of the population and restore normalcy in the shortest period
WHO Academy	International	Provides access to the WHO's COVID-19 knowledge resources all in one platform including updated guidance, tools, training, self-paced learning, and virtual workshops to boost up health-workers to take care of patients infected by COVID-19 and self-care in the critical condition
My patient sata	Germany	Detects symptoms of COVID-19, by providing a standardized questionnaire on smartphones and data given by patients analyzed by clinical IT systems providers
Vicino@TE	Italy	Allows families of hospitalized COVID-19 patients to access the clinical reports and health condition of patients. Family members can boost their moral health through positive messages
MoveUP.care	Belgium	COVID-19 patients or suspects can be coached according to the data given by them. They will receive the treatment/protocol immediately according to their symptoms (triage) by the linked doctor/hospital
Pan-European Privacy-Preserving Proximity Tracing (PEPP-PT)	International	Interrupt transmission of SARS-CoV-2 by effectively tracing infection chains rapidly via providing standards, technology

(continued)

Table 4 (continued)

m-health for COVID-19	Developer country	Description and function
EPI Salva Vidas	Spain	Coaches medical personals and state forces to use the Personal Protective Equipment (PPE) for self-protection and to protect the entire population
Triumf health	Estonia	Boosts the behavioral health of pediatric patients (7-14 yr) of COVID-19 and alleviate anxiety among children
Andama7: in-app pandemic module	Belgium	Helps citizens (especially patients, medical staff, and organization, state forces) to get updated with proper information given by trustworthy official sources. Provides medical consultation based on data collected via questionnaire
Mediktor	Spain	Provides free online self-test evaluation for Coronavirus via differential diagnosis. Also, find out other possible diseases according to the symptoms
cvPROM	Spain	Gives alerts for COVID-19 from preexisting management of Patient Reported Outcome Measures (PROMs). Helps in daily reporting by patients and/or their caregivers
COVID-19 expert	UK	Support doctors in the treatment of COVID-19 patients via clinical resources from crowdsourced information

- Surging demand for health gadgets- the fear and anxiety of the pandemic increase the use of sensor-based wearable devices and m-health applications among the peoples. Wearable provides accurate feedback on blood pressure, body temperature, and health signals that restore people's sense of control, as well as help them track their health [50].

9.3 Drug Development and Treatment

The development of therapeutic drugs and vaccines against COVID-19 is a critical challenge due to the lack of appropriate information and target. The use of computational tools, IoT, deep learning systems, and AI determines the structure and pathogenesis of SARS-CoV-2 in the human host. Genome Detective Coronavirus Typing Tool is a web-based software developed to identify the phylogenetic clusters and genotype of the SARS-CoV-2 genome and analyze in less time duration based on next-generation sequencing [51]. The use of molecular docking and molecular dynamics stimulation for repurposing the previously is used drug for targeting COVID-19 and for vaccine development [52].

9.4 Healthcare Management in India

India is the fast-promoting digitization in every field, including health care. According to the Future Health Index report of 2019, India is leading in adopting digital health technology with 76% of healthcare professionals using HER, 87% peoples with access to their HER, 80% of healthcare professionals shared this data with other associated with the healthcare industry, 46% in India use AI technologies within their healthcare practice, and 67% peoples feel easy and comfortable on digital-based healthcare technology through the use of telehealth, online consultations [53]. The Defence Research and Development Organisation (DRDO) and CSIR developed various types of equipment and technologies for combating COVID-19 and are listed as follows [54]:

- Automatic Mist-Based Sanitiser Dispensing Unit- It is based on water mist aerator technology, developed for water conservation, operates without contact, and is activated through an ultrasonic sensor. A single fluid nozzle with a low flow rate is used to generate aerated mist to dispense the hand rub sanitizer. This sanitizes the hands with minimum wastage. Using an atomizer, only 5–6 ml sanitizer is released for 6–8 s in one operation, and it gives the full cone spray over both palms so that the disinfection operation of hands is complete.
- UV-Based Disinfection Devices- Crafted and developed Ultraviolet C Light-based sanitizing box and handheld UV-C system for the disinfection of personal belongings such as cell phones, laptops, purses, money, office file cover. Defence Research Ultraviolet Sanitizer (DRUVS) was developed for sanitizing objects without using chemicals.
- Hospital Aids- It includes sample collection for testing enclosure called Econo-Walk-in Swab collection Kiosk (WISK)/High-End WISK and Kiosk for COVID-19 Sample Collection (COVSACK. It also developed Full FaceShield - Visor-Based, Medical Oxygen Plant, and Single Outlet Automatic Resuscitator.
- Mobile Virology Research and Diagnostics Laboratory (MVRDL) for remote-based COVID-19 diagnosis and testing.
- Respiratory Assistance Intervention Device: CSIR-CSIO develops a Portable Ventilator (Respi-AID) in collaboration with Government Medical College and Hospital, Chandigarh.

The Government of India has developed various other IoT-based servers, software, and platform for the advancement of digital healthcare facilities in India and is discussed below.

- AarogyaSetu- Mobilephone application developed built on a web-access platform that can use GPS tracking, Bluetooth, and proximity sensors to provide an Application Programming Interface (API) for information sharing and alert of COVID-19 proximity and management.
- Telemedicine Practice guidelines- Ministry of health and family welfare in consultation with NITI Aayog released these to legitimize the practice of remote consultation using a video call, audio, text, or email.
- National Health Stack (NHS)-A digital framework with a holistic approach to supporting digital health care based on HER, telemedicine, and m-health for Indian citizens.
- e-Sanjeevani- mobile application to support the government's plan for a pan-India telemedicine rollout.

10 Prospects and Challenges

The IoT-based healthcare system is vastly developing and used in modern times. It can help in automating healthcare workflow through healthcare mobility solutions enabling interoperability through multiple connected devices that synchronize data across each other, delivering easily accessible and low-cost healthcare management. The application of IoT for real-time data collection, segregation, processing, and delivery using an Internet-enabled mobile device for instantaneous health tracking, monitoring, alerting, and assisting patients is to provide home healthcare delivery. To motivate the full recognition of such Internet-based healthcare device throughout the aspect of human services, it is critical to identify and breakdown of precise safety and security considerations, including safety requirements, security flaws, risk models, and countermeasures, from that specific point of view. Regarding this, it is imperative to focus on the subsequent safety rations to pull off the covered service network [3]. The data privacy and security is the most significant challenge and limitation of the IoT-based healthcare system. The user data are easily prone to misuse and digitally theft, which include the duplicitous health claims, use of user information to generate fake identity, misleading with false evidence, and privacy issues. It is challenging to cumulate data for dynamic comprehensions and exploration due to the non-uniformity of data processing and communication protocols. End-users may be susceptible to malicious threats, data leakage, and malpractice upon allowing permission to third-party applications to access data. Besides, there are alternative questions about data breaches when the data ventures join the cloud storage facility of the proprietor. Internet Protocol version 6 (IPv6) is being implemented in the IoT-based system as a communication protocol to ensure confident connection among the IoT nodes in an unrelated environment through the deployment of such mechanisms.

The application of the IoT-based healthcare system brings revolutionary changes in the advancement and fastens the healthcare facilities and management. It becomes very convenient and easy to access the health data, diagnose the disease, monitor health conditions, and provide strategic treatments within low cost. The use of various computational frameworks for disease prediction conveniently increases the process of early detection and point of care delivery. The generation of the electronic health record is accessible by healthcare workers from anywhere across the globe, containing all vital information about medical conditions, allergies, previous medications, and treatment of patients. The usage of a cloud computing system is for storage, processing, and analyzing huge amounts of data into a simplified form. The remote health monitoring and mobile health make it possible to provide healthcare assistance at the extreme conditions of rural geographical areas. The development of the sensor-based wearable device, smartphone application, web servers provides its user with all necessary information such that patients themselves can track their daily health status and get advice from healthcare professionals from their home. Collectively, the advancement of IoT-based healthcare systems is the fastest growing in the medical industry and is very essential for the betterment of mankind. However, there are certain limitations, and proper training is still required in the near future to provide an error-free and convenient healthcare system.

11 Conclusion

Researchers, information technicians, and programmers across the world have tried to explore numerous technological approaches and development to improving disease prediction and treatment from current IoT-based computer assistance tools and techniques. This chapter highlighted the current strategies and available technologies of IoT-based computational framework in disease prediction and healthcare management. It focuses on the current approach of linking Internet servers and the cloud computing system with the patients' health data to generate an electronic version of it for better functioning and accessibility. With the beginning of remote monitoring technology and mobile health, it becomes easy to connect with patients all across the world irrespective of their location. The use of smartphone-based applications, wearable device sensor-based technology created evolutionary changes in the healthcare industries. Moreover, this chapter emphasizes the use of Internet-assisted technology for healthcare management and fight against the worldwide pandemic of coronavirus disease or COVID-19. The use of IoT, AI-based algorithm trained models developed for easy and fast detection of and diagnosis of COVID-19 along with the development of drugs. Additionally, this chapter established the strategies that are available and being used in India to promote the digital healthcare system. However, there are many drawbacks and limitations of IoT-based healthcare system. The availability of users' personal data may lead to privacy and security issues, and it can be theft and misuse by others for malpractice. Complete dependency on IoT-based technology may result in error within the healthcare system and even lead to misleading peoples with wrong information and fraud. The wearable devices, sensors, m-health, and other Internet-assisted computational framework might override with technical faults and dysfunctioning. Moreover, appropriate knowledge and training of the healthcare professional is required for the proper application and assessment of IoT-based technologies. Thus, this chapter overviews the various computational frameworks that are presently available for IoT-based healthcare system and opens a vast area of future research to overcome the problem of data security, privacy, and for the advancement of technology.

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SmartHealth: IoT-Enabled Context-Aware 5G Ambient Cloud Platform

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1 Introduction

Healthcare big data term is given to the voluminous electronic health records (EHR) datasets collected from hospitals, clinics, social networks, and other health-related journals and websites. This data is known for its complexity in context and is difficult to manage for building a knowledge economy for future over cloud, mobile, and IoT networks. Traditional software and hardware fail, as its computation becomes overwhelmingly challenging not entirely because of its volume but is affected due to diverse data types and high computational speed required for analyzing and interpreting for automated decision making to aid clinicians and medical experts. All the variety of clinical data evolved from hospital management information systems are made over Computerized Physician Order Entry (CPOE) for decision making in form of clinical compiled reports, medical imaging, videos, laboratories, prescriptions, pharmacies, drug details, cost, insurance. Furthermore, other data types can be found in electronic patient records (EPRs) and vital signs may also be collected through machines and sensors from monitoring by mobile apps. In addition, social networks,

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_3

tweets, RSS feeds, blogs, comments, websites, Facebook, or Facetime, patient data in emergencies, news feeds, and healthcare journals represent heterogenous healthcare big data.

The big data analytics integrated with cloud provides a storage capacity for health care that promises to enhance quality of health care with shared resources and sinking cost at the same time. Various healthcare capabilities emerge like disease surveillance for prediction, decision support, and precision medicine for population health management to provide diagnostics and treatment at every region where technology reaches with uniformity in cost. Reports with worldwide access on medicalcare data show that US residents alone generated more than 150 exabytes in year 2011 with capacity of reaching up to zettabytes (1021 bytes) and beyond to yottabytes (1024 gigabytes) in near future [1]. Complexity of big data is well recognized in health care for computation of massive electronic health records that is hard to manage by the traditional software and hardware. For personalized care in prediction, detection, diagnosis, treatment, and health management, the extreme computation is required to analyze the heterogenous data that is not just voluminous but is being generated in velocity having variety of data types and temporality based on location and time. Now, with technological evolution in big data analytics, cloud computing, 5G mobile, and IoT sensor networks, an opportunity is there in studying this massive data generated in health care through clinics and hospitals, mobile apps, IoT devices, and social networks. Finding patterns and trends within data is main aim to provide universal diagnostic solution for investigating several chronic diseases as diabetes and liver cirrhosis being referred here to improve medical care for humans' well-being with finding ways to distribute it at uniform cost while saving time.

In [2], the authors present a reformed term of SmartHealth realizing progress toward Learning Healthcare System (LHS) by Mayo Clinic in Rochester, USA. SmartHealth context aware cloud platform would encompass big data analytics to provide medical facilities at patients' locations or at a convenient point. Taking it forward SmartHealth cloud is envisioned to be connected to Internet of Things (IoT) over social platforms residing over smart apps, bio-sensors, or mobile networks. It would work as healthcare community cloud to enable context-aware services where it is required. The energy-efficient 5G SmartHealth cloud platform integrated with IoT infrastructure would be the source of generating big data from patients. The overwhelmingly challenging computation would then be required to analyze this complex data that has diverse data types within nested classes representing the major entities involved in healthcare processes. The risk associated to it is the human health, therefore, it is expected to be flawless with hundred percent accuracy.

Healthcare informatics is already a specialized domain working to come up with personalized services in form of disease predictions, detections, diagnostics, preventions, and treatments through data mining enabled with ambient capabilities. Data modeling is done by identifying patterns in patients' profiles and medical history maintained by physicians in clinical setup. Stakeholders in health care comprising of medical doctors, patients, medical staff, facilitators, hospital administration, and other governing bodies like WHO and NHS require lot of patience, commitment, and selflessness to reach the cure. Adoption of big data analytics and machine learning approaches by LHS already took much time to impact the medical field that was not fully aware of the journey toward future precision medicine for individualized health care through learning from personalized information. Medical-care industry has abundant data involving inputs from doctors, patients, and nurses of symptoms, drugs, diseases, treatment procedures, research, and more. Healthcare domain experts have now realized to bring the expertise of technologists for investigation of patients suffering from several diseases and creating long-term solutions through learning and updating the knowledge bank. The future is foreseen integrating SmartHealth analytics with Cloud Intellect (Ci) to perform as context-aware 5G platform.

This chapter is divided into eight different sections. Section 1 is an introduction of what big data health care is composed of and how analytics may be embedded into the cloud to assist doctors in intelligent decision making. Section 2 puts light on current work being carried out at Mayo Clinic under WHO since 2015 and the interest of researchers to extend it to form SmartHealth energy-efficient 5G context-aware cloud platform. Section 3 explains the 5G cloud platform envisioned by researchers to hold the analytics. Section 4 focuses on the problem domain found in traditional diagnostics of diabetes and comorbidities formed with it especially liver disease. Section 5 then defines the main aim and objective of research and highlights the need of structured data model to feed synthesized information to the analytics as depicted in simulated cloud model. Section 6 elaborates the research methodology and informs about challenges that may create hindrance in research and the path formed by researchers to achieve their objectives. Section 7 evaluates the proposed simulation model through comparison with other simulations presented in past. In Sect. 8, the chapter summarizes with future considerations on where this research may lead.

2 Learning Healthcare System

With the advent of community clouds, 5G networks and introduction of term "big data," the foundations for learning healthcare system [3, 4] were laid down. Healthcare informatics is already a specialized domain working to come up with personalized services in form of disease predictions, detections, diagnostics, preventions, and treatments through data mining enabled with ambient capabilities. Data modeling is done by identifying patterns in patients' profiles and medical history maintained by physicians in clinical setup. Stakeholders in health care comprising of major entities are clinicians, patients, paramedics, laboratories, administrative staff linked with standards setting bodies like World Health Organization (WHO) and National Health Sciences (NHS) requires lot of patience, commitment, and selflessness to reach the cure. Adoption of big data analytics and machine learning approaches by LHS already took much time to impact the medical field that was not fully aware of the journey toward precision medicine [3] for everyone finding the cure through learning from his/her personal information and medical history.

Healthcare big data [5] and its heterogeneity itself becomes the bottleneck for its analysis and conversion into information, knowledge, and finally into a well-informed timely decision that would impact infinite lives. Healthcare domain experts have now realized to bring the expertise of technologists for investigation of patients suffering from several diseases and creating long-term solutions through learning and updating the knowledge bank. The promise of its emergence into reality is conceived through evolving technologies [6] in data science such as unsupervised and supervised learning to model unstructured data retrieved through natural language processing (NLP) using Spark, Hadoop, and Flink to find hidden patterns forming graph analytics [1, 6] or sequential patterns for parallel processing.

On a detailed review of the infrastructure for LHS, it is observed that it needs to access data from EHRs or present as free text at other platforms for application of healthcare analytics having NLP capabilities. Big data infrastructure integrated with LHS seems possible looking at SmartHealth-simulated hybrid cloud. IBM Watson would be able to perform analysis with NLP capabilities over EHRs for making clinical practices more effective. Mayo Clinic empowered LHS is researching on implementing NLP run over big data [7] that reads clinical notes and documents in FHIR HL7 format in Java Messaging System over Unified Data Platform (UDP). MEA Decision Support System (DSS) works with this visualization to give recommendations for personal care as part of clinical practice [8].

AskMayoExpert (AME) is a web application is there by Mayo Clinic introducing 115 care process models (CPM) that scored 40 factors estimating risk for choosing right intervention for every CPM. Patients data is manually input and scoring tools let protocols be reviewed in AME to define correct procedure for the patient [8]. The success was accomplished when Mayo Expert Advisor (MEA) formed three working CPMs for congestive heart failure, hyperlipidemia, and atrial fibrillation in pilot phase [8].

Having knowledge of LHS [8] and its ongoing implementation at Mayo Clinic to begin with, this chapter proposes to interlink all the healthcare providers universally over a shared common cloud platform. The complexity is well understood as the healthcare domain is vast and huge risk associated with it. Therefore, the research is being carried out in various healthcare domains simultaneously by coordination of healthcare providers and technological community in support of WHO and international standards body for healthcare that is HIPAA helping to converge into universal standardized LHS.

3 Energy-Efficient 5G Secure Social D2D Cloud Intellect for Diagnostics

In 2012 [9, 10], an innovative architecture for trusted cloud infrastructure named as Cloud Intellect (Ci) was proposed (Fig. 1) to achieve ambient intelligence for

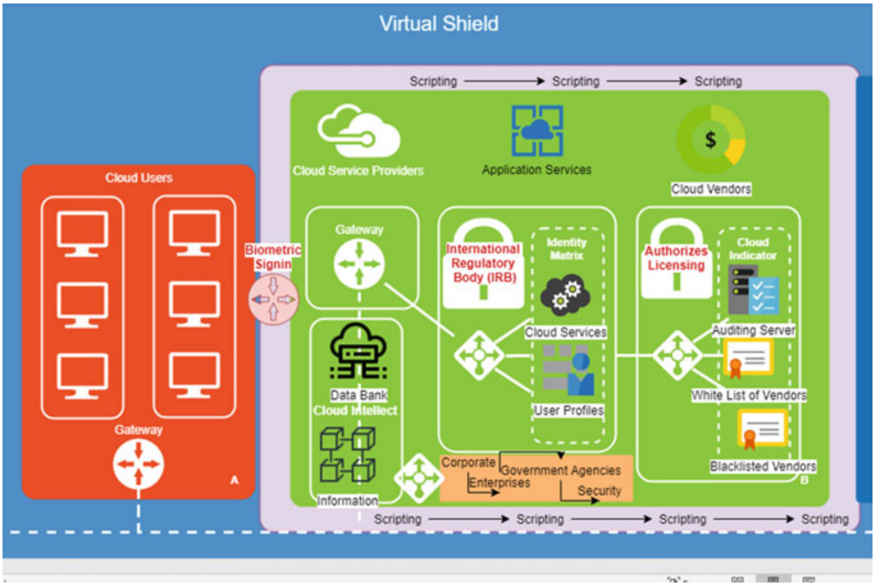

Fig. 1 High level architecture for cloud intellect

knowledge economy for United Nations Sustainable Goals. The proposed framework corresponds to a centralized architecture that provides a single platform to cloud users and cloud service providers to interact securely through signing into Identity Matrix (IMx) for identification and monitoring purposes. It also ensures that users data coming from different sources is kept confidential its integrity intact to undergo computation. The interest groups are filtered based on locality and time scrutinizing the target audience [11]. The framework is capable to dynamically refine itself making an intelligent knowledge base termed as Cloud Intellect that would enable all communities whether health care, banking, education, etc., to securely [11, 12] exchange information-related services. This chapter extends this framework to demonstrate social 5G D2D cloud network to enable context-aware community secure communications whether it is crime monitoring, traffic control, or personalized medicine such as SmartHealth discussed through a simulation model. This allows the correct people to access right information at the exact time enabling various community organizations to make relevant decisions depending over a globally securely connected 5G network of trusted peers residing over mobiles smart devices. With the advent of community clouds, 5G networks and introduction of term “big data” the foundations for learning healthcare system were laid down. Healthcare informatics is already a specialized domain working to come up with personalized services in form of disease predictions, detections, diagnostics, preventions, and treatments through data mining enabled with ambient capabilities. Data modeling is done by identifying patterns in patients’ profiles and medical history maintained by physicians in clinical setup. Stakeholders in healthcare comprising of medical doctors, patients, paramedic staff and nurses, facilitators/attendants, administration, and other regulatory bodies like WHO and NHS require lot of perseverance, commitment, and selflessness to reach the proposed objectives.

Extending this framework to demonstrate social 5G D2D cloud network [13] enabling context-aware community secure communications whether it is crime monitoring, traffic control, or personalized medicine such as SmartHealth discussed through a simulation model is presented in Fig. 4.

3.1 SmartHealth Context-Aware 5G Ambient Cloud Platform

Next generation computation is taking shape with 5G Mobile Community Cloud Networks and health informatics is taking pace to integrate itself via mobile and social health [14, 15] over IoThNet cloud platform [16] enabled with intelligent data analytics [6, 17, 18] governed by data mining and machine learning principles. Furthermore, SmartHealth [19] is visualized to be recognized by WHO as part of LHS [3, 4]. 5G health platforms are meant to connect patients and doctors outside of clinic via facilitators or nurses in nearby premises. Social or societal health networks expedite communication not only for patients and doctors but also connect patients to each other who are fighting similar health problems. Patients are now becoming aware of rare chronic diseases as endocrine, cancer, and cardiac disease while networking over social platforms to share similar experiences. Monitoring systems for public health are there for prediction of possible dengue attack or risk of asthma in a polluted environment. Therapeutic mobile treatment [15, 20] is considered to prevent depression or anxiety during sick-ness and managing behavioral disorders in diabetic cases to enforce an uplift in the lifestyle of patient.

The conceptual architecture and data model for big data healthcare analytics over cloud is a well augmented cloning of traditional healthcare system [5]. The key difference is felt when the highly efficient resource sharing and processing mechanism is seen. In a traditional healthcare informatics, business intelligence tools were being deployed on a standalone system. High-end processing of "big data" over cloud requires to be distributed over multiple nodes for execution [21] in an extensively large network. Redefining healthcare networks is required [22] as data gathers from internal and external sources to reside at multiple places. This communication infrastructure is available [16] as part of IoT healthcare network (IoThNet). Prominent data sources include [5]:

- Data obtained through various social media platforms; Twitter, Facebook, LinkedIn, websites, and blogs related to health.
- M2M data: machine sensors and other vital signs reading devices.
- Transactional big data records are available to claim for medical [6], insurance and bills in semi- or unstructured formats.
- Scans of fingerprints, retina, DNA, handwriting or blood pressure and other diagnostics biomedical data.

- All human generated reports: unstructured or semi-structured data in form of paper documents, electronic medical records (EMRs), physicians' notes, and emails.

Still it is a known fact that healthcare diagnostics are even challenging for industry practitioners and doctors so how would our healthcare analytics application would provide near to 100% accuracy in diagnostics of chronic diseases like diabetics and liver cirrhosis or other linked medical issues to these. Therefore, SmartHealth platform would be semi-supervised and continuously adapt with experts and physicians' feedback. The exploration [1] of several healthcare analytics platforms is done rigorously for finding the convergence point to form the basis of SmartHealth [19] to strengthen LHS [3, 4] vision. The adoption of standard [23] healthcare conventions given by ANSI [24] and international standard bodies as World Health Organization (WHO) [25] in form of Health Insurance Interoperability and Accountability Act (HIPAA) is missing [26].

4 Understanding Problem Domain for Healthcare in Case of Traditional Diagnostics of Diabetes Mellitus with Underlying Diseases

4.1 Diagnosis of Diabetes Mellitus

In case of Type 1 Diabetes, symptoms are suddenly felt that leads a patient into checking blood sugar in most cases. In other forms of diabetes that may be type 2 diabetes or other prediabetes, the symptoms may not be felt and left undiagnosed; therefore, prospects should be very careful [27]. The main complication of prediabetes is that it may develop into type 2 diabetes if mismanaged.

4.2 Major Causes of Diabetes

The major causes of diabetes are:

- Obesity—that often becomes the reason for fatty liver resulting in diabetes and later may become chronic and form cirrhosis or liver failure.
- High blood pressure
- Smoking and alcohol
- High cholesterol
- Sedentary lifestyle.

4.3 Formation of Diagnosis of Diabetes

Based on detection of some of the given symptoms in Table 1 that may cause diabetes mellitus Type 1 or Type 2, doctor's appointment should be considered and get the necessary tests (Table 1) done. There are mostly three cases: (i) diabetes type 1/type 2 positive, (ii) prediabetes positive or (iii) no diabetes.

Complications of prediabetes are that it may develop into type 2 diabetes if mismanaged.

Based on the high-risk factors given in Table 1, one should always be cautious and get a screening test done in every three years' time (Fig. 2). A complete diagnostic algorithm extracted from [28] is given in Fig. 2.

4.4 Complications from Diabetes Resulting in Comorbidity Diseases

Recently, it is being debated that diabetes is found to initiate several other underlying diseases if left undiagnosed or is mismanaged. Relationship is found in formation of diabetes mellitus from liver disease that may lead to liver cirrhosis and further leading to hepatogenous diabetes and liver failure [29]. Another relationship mentioned in [30] is between diabetes and chronic kidney disease.

If diabetes is diagnosed, patient needs to take care and be very cautious of keeping their glucose level in control or long-term diabetes would form with certain issues that may develop into chronic diseases [27], liver cirrhosis, etc., as discussed here.

Major complications that may arise are:

- Cardiovascular disease
- Nervous breakdown (neuropathy)
- Kidney disease (nephropathy)
- Damaged eyesight (retinopathy)
- Damaged foot
- Skin disease
- Hearing impaired
- Alzheimer.

Known underlying diseases that may result from these complications are:

- Gestational diabetes
- Monogenic diabetes
- Diabetic coma
- Diabetic hyperosmolar syndrome
- Diabetic hypoglycemia
- Diabetic ketoacidosis
- Diabetic kidney damage
- Diabetic nerve damage
- Diabetic eye damage.

Table 1 Diagnostic measures for Type 1 and 2 diabetes [27]

Symptoms for type 1/type 2 diabetes	Risk factors	Tests for diagnosis	Diagnosed positive	Diagnosed prediabetes	Diagnosed negative
Increased thirst	BMI higher than 25	Glycated hemoglobin (A1C) test	A1C level equal or higher than 6.5 in two tests indicates patient as diabetic	Having A1C in range of 5.7 and 6.4 signals prediabetes	A1C below 5.7 is normal
Frequent urination	With risk factors such as high BP regardless of age	Random blood sugar test (Incase A1C for some reason is not done)	200 mg Random blood sugar per deciliter or 11.1 mmol per liter or higher is signal for diabetes	–	–
Extreme hunger	a sedentary lifestyle	Fasting blood sugar test	Having 126 mg per deciliter (7 mmol/L) or higher on 2 tests, you are diabetic	100–125 mg/deciliter (5.6–6.9 mmol/L) is prediabetic	If fasting is < than 100 mg per deciliter (5.6 mmol/L) it is normal
Unexplained weight loss	With history of polycystic ovaries	Oral glucose tolerance test	More than 200 mg/deciliter (11.1 mmol per liter) after two hrs signals you are diabetic	Having sugar between 140 and 199 mg/dL (7.8 mmol/L–11 mmol/L) refers to prediabetes	Sugar level < than 140 mg/dL (7.8 mmol/L) indicates normal
Ketones found in urine as by-product of breakdown of muscle and fat that happens when there is deficiency of insulin	With a delivery of more than 9 lb baby	In case of type 1 diabetes urine is tested to look for presence of ketones	–	–	–

(continued)

Table 1 (continued)

Symptoms for type 1/type 2 diabetes	Risk factors	Tests for diagnosis	Diagnosed positive	Diagnosed prediabetes	Diagnosed negative
fatigue	Having diabetic history in pregnancy	There is another test for finding of any destructive immune system cells with type 1 diabetes referred as autoantibodies	–	–	–
irritable	With high cholesterol level				
vision blurred	With heart disease history				
slow-healing sores	Relative of a diabetic patient				
Infectious gums, skin or vagina	–				

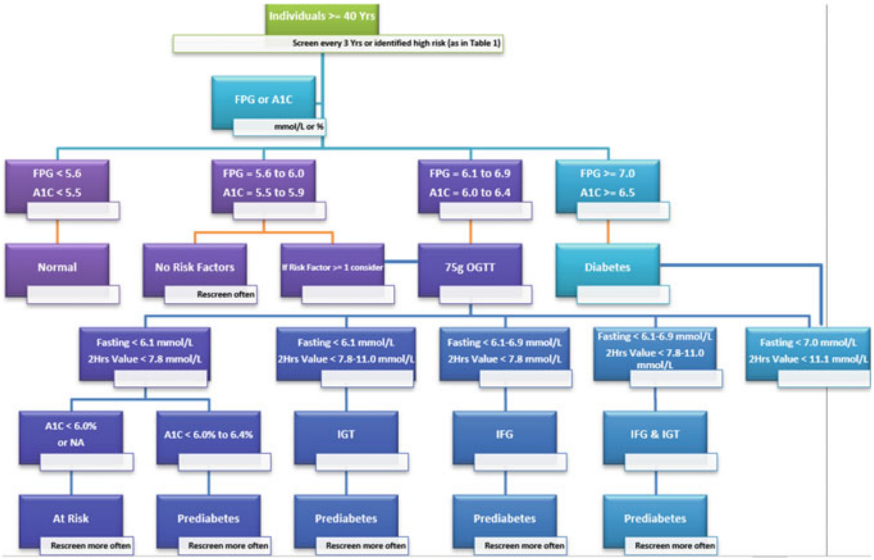

Fig. 2 Diagnostics model for diabetes

4.5 Diagnostic Model of Diabetes Mellitus with Underlying Liver Cirrhosis

Recently, it is being debated that diabetes is found to initiate several other underlying diseases if left undiagnosed or is mismanaged. Relationship is found in formation of diabetes mellitus from liver disease that may lead to liver cirrhosis and further leading to hepatogenous diabetes and liver failure [29].

Occasionally, there is chance that liver disease can be the cause of forming diabetes mellitus and vice versa if complications arise [31].

The authors of [32] present an understanding that nonalcoholic fatty liver disease (NAFLD) with distort metabolism known as metabolic syndrome (MetS) contribute to increased exposure to form cardiovascular (Heart) diseases and type 2 diabetes mellitus (T2DM). Nonalcoholic fatty liver syndrome may take effect in different age groups' mostly when they are 40 s and 50 s with chances of heart disease resulting from obesity and type 2 diabetes. Its worst case is known as nonalcoholic steatohepatitis that is liver inflammation which tends to be scary and irreversible moving toward liver cirrhosis or liver failure if not managed.

Diabetes [31] formed as complication of liver disease may lead to liver cirrhosis, hepatitis, post-orthotopic liver transplant, fulminant hepatic failure, and hepatocellular carcinoma.

However, diabetes and liver disease are seen to overlap [33], and thus, diabetes mellitus [31, 33] itself can sometimes be the cause for liver disease in form of glycogen deposition, steatosis and nonalcoholic steatohepatitis (NASH), fibrosis and cirrhosis, biliary disease, cholelithiasis, cholecystitis, and complications of therapy of diabetes (cholestatic and necroinflammatory).

Occurrence of diabetes is greatly noticed in USA and its associated complications linked to various forms of liver disease [34]. Liver disease [31] as coincidental occurrence due to diabetes mellitus and glucose homeostasis abnormalities has forms like hemochromatosis, glycogen storage diseases, and autoimmune biliary disease.

Further in [35], it is concluded through a review that there is high ratio of forming hepatocellular carcinoma (HCC) where the incidence of type 2 diabetes mellitus (T2DM), metabolic syndrome and nonalcoholic fatty liver disease (NAFLD) is found in patients. The pathophysiology is thus given a lot of focus to come up with more rational and targeted treatments for T2DM that may lead to HCC while developing NAFLD in between.

In recent study [29], as in Table 2 in this chapter, researchers are separating diabetes mellitus and hepatogenous diabetes concluding that liver cirrhosis can lead to hepatogenous diabetes where type 2 diabetes is developed before onset of cirrhosis. This type of diabetes can be diagnosed by glucose-level test. The studies imply that due to liver failure, a toxic pressure is exerted on pancreatic islets and β-cell dysfunction occurs. These patients have normal fasting glucose and hemoglobin A1c levels while their response to oral glucose tolerance test is abnormal. It is not easy to differentiate between DM and hepatogenous diabetes. The relationship can be such that DM leads to liver cirrhosis that further forms hepatogenous diabetes.

Table 2 Hepatogenous diabetes distinguished from T2DM through features found in cases having chronic liver disease [29]

	Hepatogenous diabetes	Type 2 DM
Onset	After cirrhosis onset	Before cirrhosis onset
Presentation	Subclinical DM (normal FPG and HBA1c, abnormal response to OGTT)	Overt DM (increased FPG and HBA1c)
Hypoglycemia and MALA	Higher chances of occurrence	Lower chance of occurrence
OLT effect	Revert or amelioration (?)	Persist
DM having traditional risks	Less frequent	More frequent
DM complications	Lower chances	Higher rate
Complicated liver disease	Higher than in non-diabetic cirrhotic subjects	Higher than in non-diabetic cirrhotic subjects
Mortality	Higher than in non-diabetic cirrhotic subjects	Higher than in non-diabetic cirrhotic subjects

4.6 Diagnostic Challenges for Diabetes and Underlying Liver Cirrhosis

The criteria of diagnosis vary from disease to disease. Here, when association between diabetes and liver disease is studied [36] to measure a long-term glycemic control, the criteria for diagnosis is same as ordinary primary diabetes and without chronic liver disease (CLD). In total, 2 h post 75 g glucose blood sugar levels and fasting are needed for diagnosis.

Liver cirrhosis is formed on set of type 2 diabetes, but in progression of liver cirrhosis, the type of diabetes mellitus formed is known as hepatogenous diabetes (HD) [37]. Neglection of mentioning hepatogenous diabetes and not getting proper consideration is often felt. It is associated with chronic liver disease (CLD), pancreatic dysfunction, interactions of glucose metabolism and hepatitis C virus, and genetic vulnerability. Its increased rate of surfacing is in cases with liver complications and hepatocellular carcinoma reducing response in HCV-infected patients and decreasing life span less than five years. With all its criticalities, HD is being neglected by American Diabetes Association.

Difference between hepatogenous diabetes (HD) and diabetes mellitus (DM) can be characterized based on:

1. Unlike, the traditional T2 diabetes mellitus, HD is not as much associated with risk parameters, like age, family history, and body mass index of diabetes
2. With HD, there is less chance to have macro- and micro-angiopathic complications
3. HD is associated more with hypoglycemic episodes as result of impaired liver function
4. Time of diagnosis for DM and liver disease is very crucial in differentiating HD from DM.

4.7 Continuous Monitoring and a Comprehensive Management Plan for Diabetic Patients

When underlying diseases manifest from diabetes, it is often due to mismanagement and ignorance of treatment plan by the patient. If goes untreated or mismanaged, formation of hypoglycemia or hyperglycemia may become the life-threatening cause of diabetic coma. In this case, natural responsiveness to sounds, sights, or other stimuli gets diminished and if left untreated becomes fatal. To prevent it, you must get diabetes treatment plan and stick to it. It consists of routine examination by doctor and following a diet plan. Diagnosis of diabetic patient is spread between a time span and during the process patients are continuously being guided through a follow up plan for managing their condition and monitor their routine treatment plan. If the patient is not capable enough to understand, then some family members or facilitators like nurses are guided about their condition and how to respond in case of emergency.

4.8 Shifting from Traditional to Automated Investigative Diagnostic System for Diabetes and Underlying Liver Cirrhosis or Other Chronic Diseases

Finally, as the complexity of traditional diagnostics for diabetes and its comorbidities is understood, the technology experts offered their service to automate the system in form of LHS [8]. LHS is extendable to SmartHealth going through continuous iterative computation. The optimum investigative diagnostic system for assisted living of diabetic patients threatened by comorbidity diseases occurring as complications like liver cirrhosis discussed here is yet a challenge.

Therefore, following stepwise issues in traditional healthcare system are elaborated that need a concrete solution.

1. Standardized universal data model for SmartHealth diagnostic system [2] for diabetes leading to liver cirrhosis is required that is effective as well as efficient.
2. Automated diagnostic system primarily for diabetes and its comorbidities majorly liver cirrhosis needs to be worked upon.
3. To find an optimum big data healthcare analytics technique for diagnostics remains a challenge.
4. To develop real-time heterogenous big data testbed overlapping multiple platforms where patient data is inputted for diagnostics to validate using simulated results.
5. Universally standardized investigative diagnostics system as part of LHS is not yet on cloud that must be integrated with IoT devices connecting patients, facilitators, and medical specialists to form a social context-aware cloud platform as mentioned in [2].

5 Aim and Objectives of Research

This research intends to provide semi-supervised learning for universal diagnostic system for diabetic patients suffering or at risk of forming underlying other diseases like liver failure, chronic kidney disease, etc.

1. A semi-supervised learning heuristic for diagnostics is required using a testbed having heterogeneous diagnostic data from various sources that may consist of biosensors, IoT devices, social networks, hospitals, and laboratories.
2. To develop an optimal big data healthcare analytics system using heuristics for diagnosis of diabetes and its underlying diseases.
3. Evaluation of proposed technique would use an experimental setting using real-time data on simulated testbed.

5.1 Data Modeling

An optimal healthcare data analytics for diagnostics need a generalized data model that may adapt to varying diagnostic mechanism later. Primarily, the system would need to interpret standard nomenclature understood by healthcare practitioners. Routine clinical assessment often uses below terms:

- **Electronic Medical Record (EMR)** is collection of automated patients' data from their medical history kept in any medical institute. The stored information of patient is an asset of the provider hospital that may be used outside by referred clinicians, laboratoriess or pharmacists.
- **Electronic Health Record (EHR)** has priority over EMR. It is a lifetime composition of patient profile with medical information to be shared with multiple healthcare institutes. A future is envisioned for common EHR store by Health and Human Services (HHS) that would authorize patients to share their medical history transparently to other healthcare providers for feedback.

The real outcome is envisioned through practice management system where researchers would feed provider-centric EMRs into patient-centric EHRs to support evidence-based/precision medicine. Therefore, for research in recent years EMR is highly adopted and gained tremendous value for:

Government Endorsement: US department of HHS, in July 2004, came up with a 10-year plan to establish National Health Information Infrastructure (NHII). This plan states that EHR of every American would be linked to a newly formed network of health records nationwide initiating quantum leap toward patient power, doctor recognition, and effective as well as efficient medical care.

Standard Health Record Model: work on standardizing EHR model with use of HL7-HIPPA—an ANSI standard, for healthcare industry is commissioned by HHS to the IOM. The initiative assisted in forming collaborative EHR that would bring broad-based conglomerate happen to be private and public healthcare sector responsible to generate data models for IOM approval. Standardized EHR model would best work as decentralized at NHII where it would improve effective data sharing among stakeholders.

Standard Nomenclature: even at decentralized level, uniformity is required to meet internationally set standards like ICD-10 for clinical information system and data analytics for possible interactions internationally. This goal was well received on signing of five-year contract between the National Institute of Health National Library of Medicine and College of American Pathologists for giving license of Systematized Nomenclature of Medicine–Clinical Terms (SNOMEDCT). The contractual agreement broadened the sharing of machine readable, rich clinical terms for standard classification of diseases.

The healthcare domain is known for richness of information, but to transform it into knowledge is much challenging. Therefore, the effective techniques that may be applied by tools are discovered through experimenting and finding hidden relationships and trends in given datasets. Here services of skilled resources would be required for their acquaintance with medical jargon, in implementing knowledge discovery in databases (KDD) for any healthcare organization. Effort spent on KDD [32] must be well-organized for determining hidden or unknown information from extraction of meaningful data. KDD is effective in determining meaningful and related patterns in data to form strategic solutions [38] implementing effective data mining and advanced machine learning steps [32, 39] where specific algorithms are applied for pattern extraction in data to interpret it with increased efficiency.

The overlap occurs when machine learning and data mining are mentioned as at some both fields facilitate each other whether it is classification or clustering of data using algorithms like k-means or C4.5 [32]. Data mining perceives previously unknown information using machine learning since 1960s using clustering, classification, and rule association for knowledge discovery [1]. Machine learning algorithms execute, evaluate, or predict results of any automated system on previous information that acts as a training set.

Numerous critical questions are there concerning clinical assessment of patients explained through evaluating associations and justifications from analysis of millions of EMRs. Queries mainly revolves around analyzing patients phenotypically for possible tests that may be recommended and predicting diagnosis based on results, finding possible disease for given health-related problems with highest confidence level.

Data is processed in several ways. Moreover, online analytical processing (OLAP) is one way ensuring a multi-dimensional capacity.

Patients' profiles and medical histories may be grouped in clusters to form taxonomies of related diseases because of similar characteristics and results. For best treatment strategy, empirical classification [3] is found better that uses predicted results to formulate its outcomes and learn. The best possible treatments are learned through understanding the mechanism of disease and its characteristics affecting patient to know the response and any risk of side effects in advance. This learning approach is used to reproduce these mechanisms to treat patients efficiently in diversified settings while updating itself. Inductive reasoning through pattern recognition [3] opposite of deductive reasoning learns from observing and visualizing logical models for intelligent decisions. These learned approaches are validated through testing the outcomes and feedback.

5.1.1 Universal Data Model for Diagnostics

Previous research studies [20, 22, 40] propose various healthcare analytics data models as PARAllel predictive MOdeling platform (PARAMO) [22], and platforms as multi-level data analysis (MLDA) [40] and PADSS [20] for predicting, detecting, diagnosing, and treatment of various diseases. The data model proposed in [41] outlined the limitations of current system visualizing the problems faced by Comprehensible Knowledge Model for Cancer Treatment (CKM-CT) during its definition. In [41], the authors acknowledge technologies needing for full support of clinicians and healthcare domain experts to devise a unified data model. Healthcare knowledge

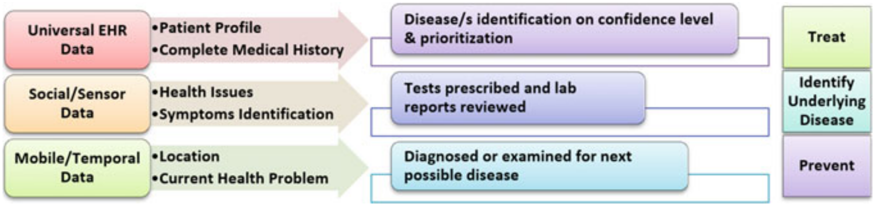

Fig. 3 Universal healthcare analytics data model

domain experts of Shaukat Khanam Hospital, Pakistan, received due recognition for making the retrieval of raw patient data possible as EHRs to transform it into standard structured nomenclature applying Classification and Regression Trees (CRT) algorithm implanted in CKM-CT model. CKM-CT is a uniform model with some shortfall because of unavailability of hospital infrastructure equipped with latest technology. Lately, the focus is on the application of advanced machine learning algorithms in combination with deep learning tools and techniques as presented in [2] over the standard big data model for diagnostics (Fig. 3) to become part of context-aware SmartHealth cloud platform proposed in [2, 19]. The data model given below shows heterogeneity of patients' data becoming input into cloud coming from various platforms, hospitals, social networks, or smart mobile devices, and biosensors as structured and unstructured temporal data. The confidence in proposed model is reached by studying different platforms for healthcare analytics in cloud context as in Predictive Analytical Decision Support System (PADSS) [20].

5.2 SmartHealth Hybrid Simulation Model

SmartHealth context aware cloud [2, 19] would best simulate over a high-performance cloud platform to process healthcare big data. To develop our research and make our consensus clear, proposed healthcare platforms have been studied as stated in [42–45].

The increase of diabetes was seen in Morocco and was known as a chronic disease making strong roots all over the world ranging to 382 million patients [44]. In total, 50% population is most of the time unaware of the disease until symptoms become visible when its late. Diagnosing diabetes is complex and expensive which Morocco sensed and initiated CASANET project for CEP.

Capitalizing on benefits was required gained from both projects which formed "ecosystem of care" as "SelfServ" for continued surveillance of patients. SelfServ builds a connection of patients with the doctors, and to facilitate this communication, the facilitators in form of friends, family, and neighbors are present on the social platform over the cloud application. The patients are also being monitored through wearable sensors by doctors having surveillance apps to respond to alerts and complex events occurring in timely manner. The doctors can create an alert among the facilitators to get to their patient in minimum time.

The SmartHealth simulation model has cloud processes and events depicted as Discrete Event System (DES). An agent-based simulation further maps entity of doctor/s, patient/s, and facilitator/s agents as societal social community in cloud infrastructure. Each agent has unique System Dynamic that communicates forming complete diabetic diagnostic system in a 5G D2D context-aware cloud network. This simulation model is designed in comparison to both approaches [44, 45] evaluating the parameters combined.

5.2.1 Proposed SmartHealth Context-Aware Cloud Simulation Model

SmartHealth cloud as DES (Fig. 4) comprises agents acting as patients, clinicians, and attendants. The patient agent has the system dynamics that would share the symptoms felt while alerting on sensing a critical case. Facilitator or attendant agent on getting alerts from patient agent would request the system to recommend a matching doctor. The doctor agent would analyze the symptoms, and previous laboratory results of patient would diagnose. The patient when diagnosed for diabetes or other disease would be queued for treatment; otherwise, another most suitable doctor agent would be suggested for an opinion, or there is chance that patient is discharged with some therapeutic and disease management suggestions. The agents as part of SmartHealth

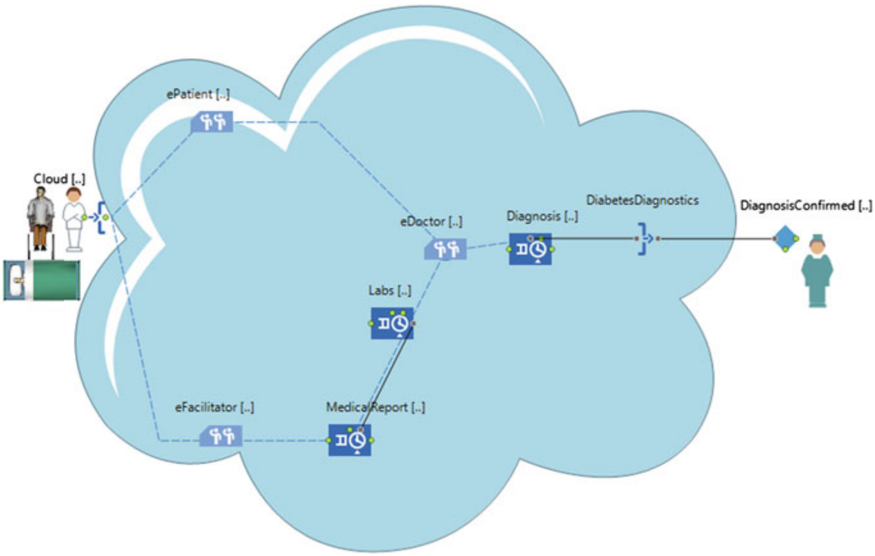

Fig. 4 SmartHealth hybrid context-aware 5G cloud simulation model designed in AnyLogic

context-aware cloud would be taking inputs from biosensors implanted on patients. In critical cases, human doctors may get involved to give feedback while updating the doctor agent.

6 Research Methodology

SmartHealth context-aware 5G cloud would extend LHS keeping in view the future vision of NHII proposed by HHS and governed by NHS standards following latest HL7 coding schema. The system is then standardizable where the simulation platform is following HIPAA coding standards and the dataset is convertible to ICD-10, HIPAA HL7 or other similar recognized coding standard by WHO or IOM.

The proposed method includes mainly four modules. First module requires hospitals dataset using globally standardized methodology of keeping EHRs of a patient with Universal ID [6] that tracks all his/her medical history of multiple visits that could relate to different diseases, laboratort tests, examinations for symptoms occurring with time.

Second module requires integration of social networks simulations taking health data through APIs of Facebook or Twitter based on users' interest in health, particularly diabetes. The data coming from biosensors and IoT devices over medical apps is also of interest.

Third module caters to development of cloud app over the web for integration of above data model, given in Fig. 3, with big data analytics. This module would be simulated over Google cloud or similar open-source cloud and IoT platform that is integrated with the international Health Level 7 (HL7) standard under HIPAA and must be in accordance with the World Health Organization (WHO) rules and governed regulations.

Finally, to enable the cloud to be context-aware, patient mobility would be gathered through mobile sensor data (Fig. 3).

All this variety of big heterogenous datasets would be spanned over a year but in different time zones to analyze historical, current, and future trend of development in patients' diagnostics of diabetes with time. The authors would consider latest dataset with broader time spectrum ranging from 5000 to 15,000 diabetic patients admitted in one hospital, in quarter one of 2013, quarter two of 2015, quarter three of 2017, and quarter four of 2019 to keep our diagnostic findings of each patient complete and current.

6.1 Research Challenges

Data mining and deep learning techniques evolving in healthcare industry benefits it to form intelligent big data analytics to be applied for emergence of:

Fig. 5 Main modules for design and implementation of SmartHealth hybrid context-aware 5G cloud

- Standardized universal data model that is adaptable to changing scenarios
- Structured treatment cost and resource availability in distributed environment
- Predicting behavior of patient based on given history
- Devising intelligent healthcare information system
- Public health informatics for practitioners as well as patients
- Implementing e-governance structures in healthcare
- use in Health Insurance System.

Healthcare big data and its heterogeneity itself becomes the bottleneck for its analysis and conversion into information, knowledge, and finally into a well-formed timely decision that would impact infinite lives. For researchers [5], healthcare data analytics pose a challenge to study heterogenous big data for finding patterns and trends within to improve healthcare saving lives at economical prices. Big data in health care has advantage over analytics in enabling them to give insights enabling decisions based on learned knowledge. While finding minimal differentiation in the algorithms and models used in conventional healthcare systems and that of big data, a huge difference is felt in user interfaces. It is earlier mentioned that big data analytic tools are less user friendly as traditional tools. Extensive programming involved makes it complex requiring diversified skills. Big data analytics tools are open source and thus are not as sophisticated as proprietary tools. In big data analytics, the enormity of data itself makes its processing complex to analyze when integrated within our proposed simulation model above.

This simulation model embedded with healthcare analytics may be used to answer several scenarios and questions that arise in terms of human health as mentioned below.

1. What is the cause of the diagnosed symptoms?
2. Which major disease can be caused with the found symptoms?
3. Which relevant tests should the application prescribe to validate the found symptoms to reach right diagnosis?
4. What is the possibility of occurrence of other linked diseases with the diagnosed disease?
5. Which other healthcare issues are found with the diagnosed disease?
6. What preventions are there for the mentioned diseases?
7. What is the ratio of patients developing these diseases through family history?
8. Does the proposed healthcare analytics app reach right diagnostics and what is the accuracy level?
9. Does the proposed healthcare analytics application comply with HL7 [26] and WHO [46] standards?

A relevant variety of healthcare analytics systems reside over different types of platforms that are spread over cloud technologies, IoT, and social networks integrated with data analytics having advanced mining and machine learning algorithms, tools, and techniques having their efficiency limited due to lack of infrastructure available.

7 Contribution of SmartHealth Community Cloud Simulation

SmartHealth simulation model that is designed in AnyLogic is validated against [44, 45] through comparison to realize that SelfServ [44] simulated platform in NetLogo used multiagent simulation environment where it combined Complex Event Processing (CEP) with Service-oriented Communities (SoC) over cloud. The strength was measured for these metrics including the metrics that calculated number of treated cases, average, and overall service time. The example taken predicted critical level of glucose alerting patient and nurses to connect patient to the doctor for relevant therapeutic response. This scenario was particularly covered in telecare service model [44] that aimed to work on future healthcare services simulation. The information system [45] for community health was also simulated in NetLogo. It also behaved as multiagent systems, and this inflexibility was deduced to be limitation posed by NetLogo. It connected patients for guidance on health insurance, whether it saves costs, on getting assistance of a good healthcare expert, for advice on getting the right treatment and care with survey on spread of disease with recommendation on therapeutic care. Mention was on two agents: assistant and human agent. Assistant agent is responsible for collecting feedbacks for healthcare services rendered and evaluates the care received. Human agent maps patient as well as doctor's role. Evaluation parameters here consist of frequency of patients that are frequently sick. The health provider's service capacity was designed for eight patients each day. Strategies were modeled for patients "waiting" or "not waiting." Patient being treated for multiple days depended on most effective strategy selected. SmartHealth cloud simulation is seen as much more efficient to function in a hybrid distributed simulation environment developed using AnyLogic platform that can integrate discrete event simulation, agent based simulation, and system dynamics together coded in C++ or Java.

8 Conclusion

This system is designed to mitigate the limitations mentioned in Sect. 7. There are critical challenges awaiting healthcare technology sector to realize and conquer to build future smart homes, cities, and infrastructure. For IoThNet [16] to be successful, there must be a solid and secure wireless network in place ensuring the data-level security and that would be fifth-generation networks. The concern is to make this data structured as described in [11]. There is need to make a standardized [20] underlying architecture for healthcare analytics to form basis of universal solution. Therefore, the chapter focuses on understanding the recent evolutions in various big data analytics platforms integrated with various traditional healthcare systems to serve patients affected by different diseases. The adoption of big data analytics and machine learning approaches by LHS already took much time to impact the medical field that was not fully aware of the journey toward future precision medicine for individualized healthcare through learning from personalized information. Medical care industry has abundant data involving inputs from doctors, patients, and nurses of symptoms, drugs, diseases, treatment procedures, research, and more. Healthcare domain experts have now realized to bring the expertise of technologists for investigation of patients suffering from several diseases and creating long-term solutions through learning and updating the knowledge bank. The promise of its emergence into reality is conceived through evolving technologies in data science such as unsupervised and supervised learning to model unstructured data retrieved through natural language processing (NLP) using Spark, Hadoop, and Flink to find hidden patterns forming graph analytics or sequential patterns for parallel processing. Previously, researchers have tried hard and contributed to solve complex problem of investigative medical diagnostics. SmartHealth system when implemented would integrate past work with current advanced data mining techniques and machine learning approaches like graph analytics, deep learning [47] to model big data for future standardized medical diagnostics. SmartHealth ambient cloud system is visualized to integrate big data healthcare analytics framework for universal use. In future, the system is set for enhancement for treating patients who are tracked for their history or would widen the diagnostics scope of diseases [48, 49] that were left out due to limited time or limitation of proposed healthcare analytics framework. Compliant to previous architectural methodologies [50], an underlying hybrid architecture [10] for SmartHealth ambient cloud [51] is seen to emerge that would be asynchronous [52] in nature for parallel processing to form the basis of cloud-based universal solution [2] validated by continuous labeling, patient data inputs, and recommendations by qualified doctors.

The future is foreseen integrating SmartHealth analytics with Cloud Intellect (Ci) to perform as context-aware 5G platform.

Acknowledgements This research is supported by Shifa International Hospital, Pakistan, (JCI Accredited-ISO9001:2008 Certified). Its consultants and research center in collaboration with MIS has contributed to provide necessary dataset for diagnostics of diabetes and all other underlying diseases.

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Internet of Things in Healthcare: A Survey of Telemedicine Systems Used for Elderly People

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1 Introduction

One of the most significant current debates is in the application of the Internet of Things (IoT) to e-health. IoT is one such application model of the Internet which connects everything with everyone. The Internet plays a vital role in modern human society. Services were provided in a wide range at any time and promised to control IoT connected devices from anywhere in the world. The telemedicine is one of the significant IoT applications that deliver immediate treatments to patients, continuously monitors critically ill patients and keeps tracks of records of each patient.

The telemedicine service providers mainly target senior citizens to enhance their quality of life. Getting older may mean that people physically and mentally unstable as compared to the young population. Therefore, it is necessary to have a system to monitor their daily activities continuously. Telemedicine-based healthcare providers' use a system to monitor patients continuously in the form of video conferencing and by monitoring basic signs such as temperature, oxygen saturation, heart rate, blood pressure, blood glucose, electrocardiogram, and weight. Moreover, telemedicine enables older people to be active in their contented phase [1], especially in homes where they feel comfortable and safe and interact with society.

Over the past century, there has been a dramatic increase in using telemedicine systems to enhance the quality of senior lifestyle. However, every technology has

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_4

optimistic and pessimistic influences. The telemedicine systems that target older people have few drawbacks as well. The major drawback is adopting time. Senior citizens are generally slow to adopt new technologies. Most of them less cognizant the use of computers and mobile phones, and it creates a technical barrier between the user and the service provider. Another drawback of this technology is that they prefer to confront the doctors and health professionals in person than talking with them through video conferencing. Breaching the privacy and security of the user is another negative factor of the telemedicine systems. Collection of personal health data and transmission of those data should confidential in order to gain their trust. Unauthorized access to vital data, such as therapeutic conditions or experimental results, can make an adverse impact on the life of the patient. Besides, a patient's health records can be used as a marketing tool, especially for insurance and pharmaceutical companies. The ethics of monitoring senior citizen's actions in the privacy of their own homes should also be considered [1]. Therefore, cost-effective, friendly, secure, and trusted IoT-based telemedicine should be implemented for elderly and disabled individuals.

IoT-oriented telemedicine provides straightforward medical solutions for various problems that arise among senior and disabled individuals in modern society. For example, they can reserve an appointment with a doctor via the Web site or mobile application. Then, the doctor recognizes the symptoms and directs the required medical tests or medicine to them by using video conferencing. This will reduce the waiting time, cost, and energy of the older people.

Most recently, the literature has emerged that offers contradictory findings of the benefits, data analyzed algorithm types, challenges, and countermeasures in recent IoT wearable devices, and services used to diagnose the common diseases and symptoms occurred in the elderly population. In order to do this, the raw data from peer-reviewed articles on the topics of IoT in healthcare, and the IEEE database was the main source. Most of the review articles examined different technical approaches of the IoT in the healthcare industry.

Bujnowska-Fedak and Pirogowicz [2] have evaluated the preferences and the attitudes of the e-health related services and the associated factors of the senior citizens in a Lower Silesia Province of Poland. The general practitioners have conducted the study on behalf of the authors by assessing 286 people over 60 years old. According to the results, 41% of the older people had an interest in the IoT-related healthcare service. They seemed more likely to use IoT in healthcare [2].

There are affordable kits equipped with various sensors to detect an individual's basic signs, such as blood pressure, heart rate, and blood oxygen saturation for developing countries [3]. As an example [4], a cost-effective smart chair equipped with sensors facilitates to monitor vital physiological behaviors of the human body and transmit the data to an android application through email/MMS/SMS or by Bluetooth.

Many authors have focused on medication management and domestic healthcare practices systems. These systems consist of an intellectual and interactive packaging as known as I2 Pack and smart medicine box (iMedBox). Jennifer et al. [5] have examined the daily body temperature and blood pressure of 10 patients who were taking oral medication. The system generates an emergency medication reminder to the patient and the physician via a wireless temperature sensor and blood pressure sensor.

Identify the discomfort and alleviate of bed-bound patients is an essential feature in the healthcare system. However, the authors of [6] introduced a mattress embedded a sensor that can be shifted and turned through an intelligent IoT system according to the patient discomfort and alleviate. A photoplethysmography sensor (PPG sensor) was used to detect the pulse waves in arterial-venous-rich areas, and then the sensor responds to the patient's feedback by changing the mattress position.

Correspondingly, in [7] has focused on novel SM-IoT platforms for patients and caregivers. These platforms have been proposed in order to promote healthcare services and to improve the services of monitoring patients in distant. The proposed system could collect the data from heterogeneous sources, integrate the data using the semantic web, store the data in the, visualize the data in interfaces and data sharing.

Some user-friendly IoT-based telemetric systems are cable of tracking bed-ridden patients. These systems regularly update the data for an example; heartbeats per minute (BPM) on the cloud server. The sensors used in the system can recognize the unusual heartbeat fluctuation and send an emergency message to a family member and a doctor's mobile phone [8]. This kind of innovative healthcare system enables to connect the patient and the doctor through live video images by using different types of sensors like ECG sensor, pulse rate sensor, blood pressure sensor, respiration rate sensor, body temperature sensor, and advanced camera sensor [9]. Some experiments [10] intended to identify the approach and model criticalities of healthcare IoT systems. They have focused on a remote monitoring platform and a smart ambulance system to send medicine via mobile services. This system targeted to dispatching the nearest available ambulance to the accident place, monitoring the patient, and sending the data to the hospital [10]. However, there has been little discussion about IoT-based organs treatment, and enhance the benefits of the devices or systems and the quality of the parameters of the devices and systems. The pilot studies showed that there was an enormous gap to be addressed in this field.

The purpose of this chapter is to review recent research into the importance of the IoT-based telemedicine for elderly life patterns. The healthcare providers, scientists, medical students, and doctors are the most beneficial parties in these studies. The findings of this study can be used to diagnose and control the critical conditions of human diseases with IoT efficiently and effectively.

This chapter has been divided into five parts. The first part deals with the introduction and the necessary information on the discussed topic. The rest of this chapter is structured in the following order. Section 2 is a description of materials, methods, and selection criterion of acquiring data set for the analysis. Data analysis tables and relevant graphs have been obtained in Sect. 3. Discussion of our findings with related literature and conclude our review along with some implications of our findings in Sects. 4 and 5, respectively.

2 Materials and Methods

To date, various methods have been developed and introduced to select the operating system and communication system for the IoT-based telemedicine systems. For this study, the methodology has been structured into several sections as followed.

2.1 Data Collection

The pilot data gathering phase was directed by collecting peer-reviewed scientific publications. The initial sample consisted of the raw data and attributes such as algorithm, encryption method, IoT hub system, operating system, communication system, sensors, storage and network system, platform and hardware were compared and tabulated. Above parameters were identified as the most significant contents of the publications reviewed to be studied and analyzed.

2.2 Data Inclusion Criteria

The data comparison table was drawn with the attributes listed above evaluating, data inclusion criteria.

2.3 Raw Data Analysis

The analyzed data were summarized into sensors, communication systems, and operating systems used in healthcare systems based on the IoT.

2.4 Analysis of Telecare System Platform, Algorithm, Encryption Method, IoT Hub System, Operating System, Communication System, Sensors, Hardware, Data Storage and Network System Data Inclusion Criteria

Table 1 provides a structured summary of the data, gathered from peer-reviewed publications.

Table 1 Structured summary of the data

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
1	Bujnowska-Fedak et al. [1]		SOPHIA, DALLAS	GSM, Video conferencing, GPS, email	Motion sensors	Cloud storage and wireless network		Elderly people and disabled people and making telecare system secure	
2	Arrizon et al. [3]			GSM, Wi-Fi	Oximeter, blood pressure sensor		Arduino open source platform	Sensor kit to measure BP, blood glucose concentration, heart rate, and oxygen saturation	Pulse oximeter and heart rate sensor have less than 10% error compared to commercial instruments
3	Ganesh et al. [4]		Linux	Bluetooth, Wi-Fi, GSM	Load sensor, blood pressure sensor, body temperature, motion sensor	Cloud, Ethernet	Arduino Open source platform	Elderly people and disable people smart chair which can detect vital signs of a person such as BP level, blood glucose level, heart rate, etc	Due to the constrain when entering API key for each subject, to eliminate that implemented custom made the webserver
4	Jennifer et al. [5]	A new generation of the intelligent processing algorithm		GPRS module with SIM slot	IR sensor, Blood pressure sensor, Temperature sensor			Use of Medbox effectively and efficiently	New embedded technologies were required

(continued)

Table 1 (continued)

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
5	Nataraj et al. [6]		Android	ZigBee and Bluetooth	PPG sensor, motion sensors		Arduino Uno	Patients with immobility such as paralysis, the final stage of Alzheimer	The accuracy of the solutions was depended on the data send through PPG sensor and noise filtration
6	Dridi et al. [7]		Android system, Spark (data processing module), YOAPY SAHHc	Wi-Fi, ZigBee and Bluetooth				Smart IoT platform for the healthcare system, using private cloud	
7	Sonnis et al. [8]		Embedded C	Wi-Fi, GSM, Internet	Blood pressure, heart beat sensor			Reduce stress on healthcare providers and reduce the cost for ECG tests and other blood tests	

(continued)

Table 1 (continued)

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
8	Divakaran et al. [9]		Embedded RTOS	Internet	Temperature sensor, Analog ECG sensor, BP sensor	Cloud storage and wireless network	ARM Cortex-M4 web sever	Web-based remote healthcare diagnostic system with a live video feed	The microcontroller was used STM32F429 microcontroller while most of the existing systems consisting of PIC microcontrollers. Due to the low power consumption of this, suitable for embedded systems
9	Kotronis et al. [10]				ECG, BP sensors, temperature sensors, motion sensors	Cloud storage		Real-time diagnosis of medical issues and remote monitoring patients	

(continued)

Table 1 (continued)

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
10	Wu et al. [11]	AES algorithm	Android IOS	GSM network, WLAN, Bluetooth		Google App Engine cloud server	HTC butterfly S with 2 Gbytes of RAM, iPhone 4 s, IoT as a service	Inform caregivers abnormalities of patient's health status via a smartphone app	Medical devices are not consisting of GPS positioning. Therefore, is hard to implement GPS positioning to the system
11	Abawajy et al. [12]	SMO-based classification algorithm, BayesNet, Naive Bayes	Android IOS	Wi-Fi, Bluetooth, GPS, ZigBee	use physical sensors such as BP, temperature, motion, ECG and use virtual sensors which are collecting sensor data from personal servers	Cloud storage, wireless network		Cloud-based architecture which can examine patient's health remotely	Proposed algorithms are not used in real life. Making an energy efficiency system
12	Mahmud et al. [13]	Integro-differential algorithm	Android	Bluetooth, Wi-Fi, GSM, GPRS	IR sensor, the EPIC sensor (ECG Sensor)	Internet, wireless network	Arduino IDE development, RFduino	Measure ECG using Smartphone	Results from ECG are not accurate as medical grade

(continued)

Table 1 (continued)

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
13	Satija et al. [14]	TP algorithm	Android	Bluetooth, Wi-Fi, GSM	ECG sensors	Cloud storage	Arduino	Development of simple SQA method for getting ECG signals	ECG signals are distorted under more intensive physical activities. ECG telemetry system consumes more battery power to give quality ECG signals
14	Metrz et al. [15]		Android, IOS	Bluetooth, Wi-Fi, GSM				Introducing wireless and use of mobile apps for healthcare system even in rural areas	Lack of knowledge to use mobile apps
15	Tsai et al. [16]		Webduino, Ubuntu	Wi-Fi	IR sensor		Arduino	Smart pill box which will help the patient to get their medicine on time	Arduino module memory is not enough, therefore, the additional memory card must be added
16	Görs et al. [17]		Android, IOS	Wi-Fi, GPRS, Bluetooth HDP, IEEE 11073, UMTS	BP Sensor, Temperature sensor	Oracal database		Designing and developing Telemedicine system for remote healthcare using COTS hardware	number of sensors must be increased in order to supervise possible diseases

(continued)

Table 1 (continued)

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
17	Salahuddin et al. [18]			Wi-Fi, GSM, Internet, ZigBee	ECG sensors, PPG sensor	Cloud storage		IoT infrastructure for the smart healthcare system	lack of standard 5G definition
18	Laplante et al. [19]				ECG sensors				Effects of electromagnetic radiation and signal strength problems. Privacy and security of patient clinical data
19	Lo et al. [20]	Signal processing algorithm		Wi-Fi, ZigBee, and Bluetooth				Use wearable sensors on patients	Privacy and security of clinical data. The high power consumption of the devices
20	Jue et al. [25]					Cloud storage		Patients with severe conditions such as cancer	
21	Petito et al. [26]				BP sensors, motion sensors			Measuring pressure of the eye	Data security and privacy can be affected

(continued)

Table 1 (continued)

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
22	Raskas et al. [27]					Cloud storage		Wireless wearable on toddlers	Technical issues, patients will take time to adapt for the conditions, need training
23	Catarinucci et al. [21]	Wireless sensor network (WSN) algorithms	Android, IOS	Bluetooth, Wi-Fi, ZigBee	Humidity, light, temperature, ECG sensors	Amazon SNS cloud service	SHS, 6LRR, and HT node architectures, HSN architecture, UHF RFID	IoT smart architecture for monitoring and tracking patients, personals, biomedical devices, etc. within hospitals and other healthcare providers	Energy consumptions, complexities of the algorithm
24	Pasluosta et al. [22]				ECG, EMG, EEG sensors, motion sensors, BP and Temperature sensors, biochemical sensors			Use wearable sensors on Parkinson's disease patients	Privacy and security of data. Energy consumption of the wearable devices
25	Khamis et al. [23]	UNSW, PT, GR			ECG sensors			Electrocardiogram recordings	Complexities in used algorithms

(continued)

Table 1 (continued)

#	Author and year	Algorithm	Operation system/platforms	Communication system	Sensors/devices	Storage and network system	Hardware/architecture	Implementation	Challenges identified
26	Mageroski et al. [24]				Camera sensors, IR sensors, Motion sensors, Touch sensors, Voice sensors			Use of wireless sensor networks to look after elderly people	Complications of wireless devices. Clinical data security and privacy can be affected

3 Results

The raw data collected from scientific publications (2015–2017 Table 1) were analyzed concerning the sensors used communication system. The graphical representations of the analyzed results are shown in Figs. 1, 2, and 3 as follows.

3.1 *Sensors Used in Healthcare Systems in Telemedicine*

According to this study results, 22% of the sensors used in healthcare systems are ECG sensors, while 7% are IR sensors (Fig. 1). The results of this study indicate that the uses of the motion and temperature sensors for the healthcare systems as 18% and 20%, respectively.

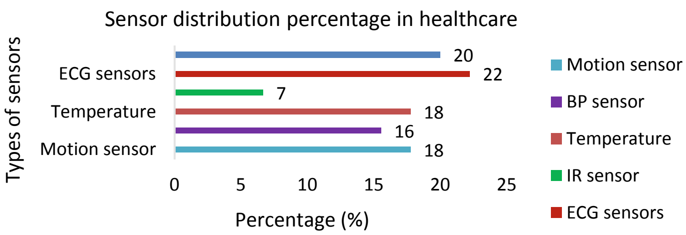

Fig. 1 Overview of BP sensor, temperature sensor, IR sensor, ECG sensor, motion sensor, and other sensors used in healthcare systems based on the IoT, using the data from scientific studies

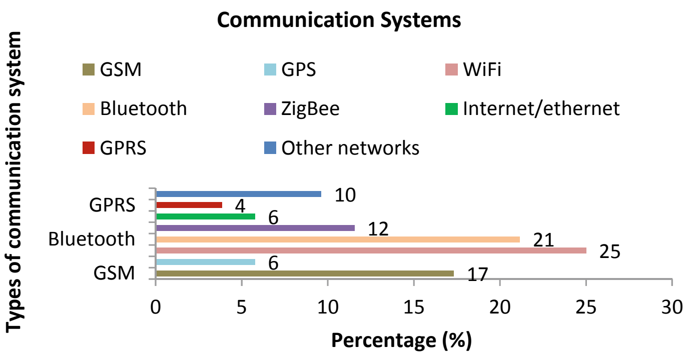

Fig. 2 Overview of GSM, GPS, Wi-Fi, Bluetooth, ZigBee, Internet/Ethernet, GPRS and other networks used in healthcare systems based on the IoT, using the data from scientific studies

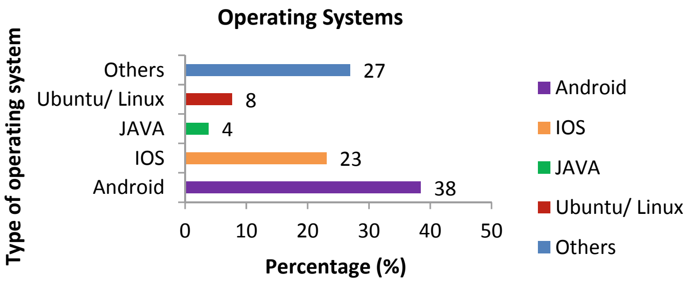

Fig. 3 Overview of Android, IOS, JAVA, Ubuntu/Linux and other operating systems used in healthcare systems based on the IoT, using the data from scientific studies

3.2 Communication Systems Used in Telemedicine

Figure 2 illustrates that 25% of the healthcare systems use Wi-Fi as the communication system, while 21% use Bluetooth as the communication system. The GPRS is the least use communication system in the healthcare system, and it was recorded as 4%. However, use of the GMS and ZigBee sensors was reported 17% and 12%, respectively.

3.3 Operating Systems Used in IoT-Based Healthcare Systems

Moreover, 38% of the healthcare systems use Android, and 23% use IOS as the operating system Ubuntu/Linux operating system was used by 8% of the healthcare system while 4% of the user implemented JAVA as the operating system (Fig. 3).

After analyzing all the results, most of the healthcare systems use temperature sensors, Wi-Fi as communication media and Android as their operating system prominently.

4 Discussion

With the socioeconomic development, prevalence of chronic diseases and comorbidities among the elderly population has been significantly increased. Polypharmacy is a usual phenomenon in the elderly population, and it has been reported 55–98% of the elderly population worldwide. Age-dependent diseases such as vascular complication dementia, atherosclerosis, osteoporosis, and osteoarthritis are common during the process of aging. These diseases induce the mental and physical alterations and resulting in continuous supervision, incentive attention of the healthcare practitioners, and family members. A considerable percentage of the world's older people are isolated and singularization due to many family issues. In 2011, census data in Canada showed that 24.6% of people aged 65 years or over lived alone while relying only on themselves. Intolerable utilization of the community services, resources cost, the steady growth of medicinal demand, and social services are directly influenced by the comorbidities among the elderly population. Recent statistics show that diagnosis and treatment cost for chronic diseases in developed countries has increased significantly. A study in 2010 reported that people in 65 years and older spend about $18,424/person for the personal healthcare system in the USA. Similarly, it has predicted that the cost of elderly caring will grow substantially in the next decades. Develop a cost-effective and precise telemedicine system can be helpful to minimize the unexpected cost for the elderly population.

Numerous research groups intended to overcome discussed issues of the elderly population and telemedicine-based care were evolved as the most probable solution. Telemedicine-based care help to achieve most of the care-based requirements of the elderly people, and the home-oriented telecare systems facilitate three primary services as (i) monitoring safety and security features, i.e., smoke sensors, and flood and fire detectors (ii) monitoring vital health parameters, i.e., heart rate, blood glucose levels, and body temperature (iii) assist for the information and communication technology (Internet, telephone calls), i.e., teleconsultations, phone-based reminder services such as short message service (SMS) reminders for appointments and prescribed medicines. The technologies such as the Internet and mobile phones in a home setting provide independent living for the elder community-dwelling adults. The assistant and the promising approach of this system simplify the elderly life and enable them to feel comfort and secure environment in their own home. The functional requirement of this setting is highly sophisticated and expensive, which is only accessible to wealthy social groups. Therefore, healthcare professionals need necessary assistance to select cost-effective telemedicine aids to minimize the user complexity of the telemedicine healthcare system. As a result, this research aims to find novel IoT-based healthcare devices, kits equipped with sensors or telemetric systems to detect signals and produce qualitative and precise information for health care professionals. Therefore, they can take steps in the prevention of diseases and provide home-based caring and assistant to the elderly people.

This study has identified the Wi-Fi as the most popular communication system of the IoT-based healthcare systems and Android as the operating system. Furthermore, the ECG sensors are being widely used in sensor kits if compared to other sensors such as BP sensor, temperature sensor, IR sensor, and other sensors. The government and private university research centers, telecommunication corporations, and administrative bodies in the worldwide are primarily involved in implementing an array of programs of services in the field of telecare intended for the elderly. For example, the "Aging-Related Support Systems for Healthy and Independent Living" is a crucial research program developed by the German government and runs on SOPHIA platform [3]. This program exploited the modern technology for the implemented a program to support living the elders in their own homes by providing a spectrum of the services including security, wrist band alarms service, installation of the smart sensors in the home, video, and audio telecommunication service. Also, the multifaceted UK program is another example of the telemedicine service. This program is usually known as Delivering Assisted Living Lifestyles at Scale (DALLAS) and enhances the elderly and disabled life quality by supporting them to survive independently in their home environment. Similarly, the Japanese research group [1] introduced a telecare system using high-tech robots to assist in daily living necessary activities for the older.

The demonstration projects and pilot studies discussed the effectiveness and practicality of the telemonitoring and telecare systems. Because these systems can identify many failures, i.e., heart failure, and facilitate "usual" specialist care as in hospitals by reducing clinic and emergency room visits and unplanned re-hospitalizations [1]. However, most authors draw attention to developing vital sensor kits that can be used to detect the blood pressure, temperature, etc., in a cost-effective way. Most experimental sensor kits have 10% error compared to the commercial kit. The authors have concluded that those sensor kits are more effective than commercial sensor kits. One of the limitations of this explanation is that it does not explain the marketing strategy [3]. The experiment of designing a low-cost smart chair has been implemented based on library research, laboratory experiments, and standardized personality tests. In that article, the author proposed a web server and android phone to transfer the results, and then, the doctor would be able to gather the feedback. They have prearranged to adding a keypad to the smart chair and reduce the complexity of the coding system by introducing a personalized webserver to the system [4]. Most of the studies showed that there are reliable, useful, and cost-effective IoT-based systems, models, and platforms which can be used for elderly patients to communicate with physicians and to send alarm signals to physicians when a risky condition occurred to a patient [6–9].

Like all technologies, telemedicine also has limitations, and some of which are self-barriers arise senior themselves. Elderly populations resist new technologies like computers and the Internet and face difficulty in using these technologies than younger people. A statistic of the computer usage of the different age groups conducted by Nielsen Norman Group found that a group study population over 65 years has 53% success rate in using online purchasing while 78% success rate for a group of younger users [1]. The age-linked cognitive impairment and motor functions as vision impairment, hearing impairment, short memory loss, and physical disability limited to absorb the new information. This fact may cause difficulty in adopting a changing environment and preventing the assimilation of new forms of behavior [2]. Communication methodology is identified as the next limitation in telemedicine. Seniors are favored to establish a face-to-face or a personal relationship with their medical practitioners, and this is another limitation to perform telemedicine-based services from a distance. A study conducted by [28] reported that 82.61% of seniors aged 60 years or over of the sampled population have a strong preference for direct contact with health professionals over the Internet.

The next barrier is finance. Many seniors depend on their pension, and pensioners are unable to purchase high-tech equipment or devices. Despite the advantages of the telemedicine, seniors are reluctant to invest the telecare, telemedicine, or telemonitoring systems. Instead of the investment, they try to depend on the service from a third party, especially government free Medicare or insurance companies for their health expenditure [5]. Access to a telecommunication/computer network can also be limited, especially in developing countries. The study proposed by [29] in Africa showed that the percentage of household Internet access and the percentage of internet users were 11% and 0.4%, respectively. Inadequate infrastructures and the Internet connectivity cost became a financial barrier to the telemedicine systems.

Older adults are always concerned about the privacy and security of their personal information, and they have a centralized fear of revealing them. Maintenance of the privacy and security of the personal healthcare data are other vital elements in a telemedicine system. Unauthorized access, integration, fabrication, and disclosure of personal data are common security breaches in information security and known as CIA triad [7]. These kinds of a security breach can be revealed crucial medical test results and negatively influence the patients' personal and professional life. Also, some pharmaceutical and life insurance companies use these personal healthcare data as a marketing tool to promote their services. A survey performed by [30] emphasized that 61% of the American seniors (aged 65 years or older) in the surveyed sample were highly concerned about the unknown personal information collectors compared with 46% of younger (aged 18–29 years).

Finally, some studies yet to be unable to trigger anxiety and advantageous of the telemedicine, especially in remote monitoring systems. The study of [31] revealed that telemonitoring of the comorbidities in frail elderly patients could be disturbed the results or sometimes can be failed. However, 14.7% of the mortality rate was reported in telemedicine, and this was 3.9% for the usual personal caring. According to this study, telemedicine is not successful to use for the frail elderly patients and has identified a significantly high percentage of harm than the benefits. The authors yet to be unable to explain the practical evidence for the differences in the mortality rate, and they suggested several intervention increments may be the reason for the differences. The synopses of the limitations of the study were identified as a technical barrier, privacy, and security, financial and lack of experiments regarding the related field. Prior studies that have noted the importance of IoT in the healthcare sector [32–34]; however, resolving security issues could be a quite challenging task [35–37].

Until now, telemedicine techniques identified as luxurious, inflexible and personalized service. However, the socioeconomic and technical development of the world tend seniors susceptible to telemedicine services more than the last two decades. They are using emerging technologies for evolving care needs. Though it is relevant to make the seniors aware of the benefits and challenges of the telemedicine systems before becoming users, further, the responsiveness of the privacy and security breaches in the e-health is a must fact.

Building family trust can be an influential factor to decide whether to use such a service or not. IoT facilitates the interaction between humans and machines. Humans can be harmful as they can expose private data to the outside world, and this is known as data breaching. Therefore, the telemetric systems should be developed on a secure and trustworthy platform. More simulation work and testing of privacy mechanism should be carried out as a future study. Future researchers should not limit to experiments that target useful sensor kits and healthcare devices. They should widen their experiments on encryption methods used in healthcare systems to protect the authority integrity and privacy of the data, hardware structures in healthcare devices and challenges of using IoT-driven healthcare systems and devices, especially for older people.

This study identifies the potential opportunities in healthcare systems with the combination of IoT. Therefore, this study aims toward taking a new step in the prevention and detection of diseases, especially for elderly people by using IoT platforms. Furthermore, the healthcare sector based on IoT requires continuous research as the world is moving forward consistent with the concept of IoT.

5 Conclusion

This study provides a review of telecare system platforms, algorithms, encryption methods, IoT hub systems, operating systems, communication systems, sensors, hardware, data storage, and network systems in telemedicine. This study is based on information gathered from 26 peer-reviewed publications. According to the findings, the highest percentage of the sensors used in healthcare systems is ECG sensors, and most of the healthcare systems use Wi-Fi as the communication system and Android as the operating system. Future scholars can develop experimental proposals toward different encryption methods used in healthcare systems, qualitative hardware structures in healthcare devices and the limitation of the IoT drove healthcare systems and devices, especially for elderly people. The findings of this research are decidedly beneficial to the healthcare providers, scientists, medical students, and doctors to diagnose and control the critical conditions of human diseases and symptoms with IoT efficiently and effectively. This information can be used to develop aimed interventions aimed at the IoT-oriented telemedicine systems.

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Remote Patient Monitoring: Health Status Detection and Prediction in IoT-Based Health Care

Azadeh Zamanifar

1 Introduction

The increase in life expectancy and the decrease in the birth rate are factors that contributed to the aging of the population [1]. The World Health Organization survey indicates that, by 2050, the number of older adults will be higher than the number of children on the planet [2]. This condition directly affects the number of people available to properly care for the elderly, whether in the informal context (family and friends) or formal context (caregivers and health professionals). This scenario encouraged the development of technologies aimed at increasing the autonomy of the elderly, using tools for self-care, and to support families, friends, and health professionals in the area of elderly health [3]. In parallel to this scenario, we have seen the growth in the adoption of mobile applications to perform everyday tasks that previously required the use of personal computers or the user's displacement [4]. For instance, with a mobile application, grocery shopping can be made in a few clicks using a smartphone, avoiding the trip to the supermarket.

IoT-based healthcare system has a high impact on mankind and society. It plays a significant role in the domain of pharmaceutical research and industry. The data involved are complex and heterogeneous, which makes them more challenging to understand and explore [5, 6].

IoT-based patient monitoring is one of the best well-known patient monitoring systems which helps people with a better healthy life [7, 8]. IoT changes the life of many people and improves the life of the patient by bringing back the patient into their homes and monitoring them remotely [9, 10]. There were many challenges regarding this. Nowadays, most of them are resolved. However, there are still some

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_5

challenges that are not addressed. Security is one of the ever-challenging factors in IoT-based healthcare systems [11, 12].

In this chapter, we first explain some basic concepts about IoT-based healthcare systems. Then, the authors explain the related issue regarding IoT-based remote monitoring. Health status prediction is another concern in this topic. We cover the most important related research in patient remote monitoring system. The state-of-the-art works that are done in this field is reviewed. We try to categorize the works so that it will highlight the ongoing research. We can classify the healthcare system into two main categories:

(1) Typical IoT-based healthcare system
(2) IoT-based healthcare system with edge computing.

IoT-based healthcare systems apply fog, edge computing [13], and serverless computing to predict the health status of the patients more accurately and efficiently. In Sect. 2, the basic concept of healthcare system is discussed. A typical IoT-based healthcare system and IoT-based healthcare system with edge computing are described in Sects. 3 and 4, respectively. Finally, Sect. 5 presents the open research and challenges and Sect. 6 concludes the chapter.

2 Basic Concept in Healthcare Systems

Biomedical knowledge has a high impact on mankind and society. It plays a significant role in the domain of pharmaceutical research and industry. The data involved are complex and heterogeneous, which makes them more challenging to understand and explore. In recent years, with an increase in the amount of biomedical data, there is a rising opportunity for exploring and learning about their interactions and effects. Data preparation is always an enormous and time-consuming task in the biomedical field. The process involves assembling data from multiple reliable sources, analyzing their statistics, and processing them into some specific format, with satisfying the requirements of the associated biomedical problem. ECG sensors are used for monitoring electrical impulses among heart muscle. Electromyography (EMG) sensor is used for observing muscle activity. Electroencephalogram (EEG) sensor is used for recording electrical activity at the brain. Temperature sensor, core body temperature, and skin temperature are designed for health status prediction by measuring the body temperature. A breathing sensor is used for monitoring respiration [14]. IoT health care provides two-directional communications between a mobile node(s) and the remote server which is not possible in traditional healthcare systems. As the infrastructure of the IoT healthcare system is mobile IP-based wireless sensor network, power constraints are also one of the challenges of this environment [15, 16]. Also, connected connectivity and low delay are the other significant challenges [17, 18].

The main goal in an IoT-based healthcare system is collecting real-time data and takes decisions about the patient's immediate help [19]. Thus, the patient must be in the range of the IoT network as a vital requirement. As mentioned, the other important issue in healthcare systems is the continuous connectivity of the mobile node(s) to the network. Health data can be collected accurately. Therefore, detecting and predicting patient health status can be done more accurately. Examples of benefits of adopting IoT e-health are the following [20]

1. People use IoT e-health for health, exercise, safety, or beauty reasons, and it has a solution for everyone's needs.
2. Smooth fusion with different technologies: IoT e-health enables different technologies to work together perfectly.
3. Ability to use big data collection and learning: This is done to efficiently analyzing the patient data.
4. Easy to use: The patients do not need any complex guidance to use the system.
5. Cost reduction: The IoT healthcare system removes the need for patients to stay in a hospital. Thus, the overall cost of continuous monitoring of the system reduces.
6. Doctors can be more involved: Doctors receive online data, and they are notified by the condition sooner.
7. Availability: The access to e-health data/services is possible at anytime and anywhere.
8. Online help: IoT e-health enables 24/7 online access to health specialists such as doctors, skin doctors, and many other professionals.
9. International working team effort: Health professionals around the world are connected via the IoT e-health community. This enables patients to have more access to international facilities at their fingertips (anywhere and anytime).

The essential factor in the healthcare system is creating an ecosystem so that all the relevant subsystems can communicate with each other. The wearable device collects data, and the collected data are analyzed at the cloud [21–23]. Figure 1 shows the typical architecture of the healthcare system.

As it is shown in Fig. 1, there are three main components: (1) body area network, (2) gateways, and (3) cloud and big data storage. This platform provides services to

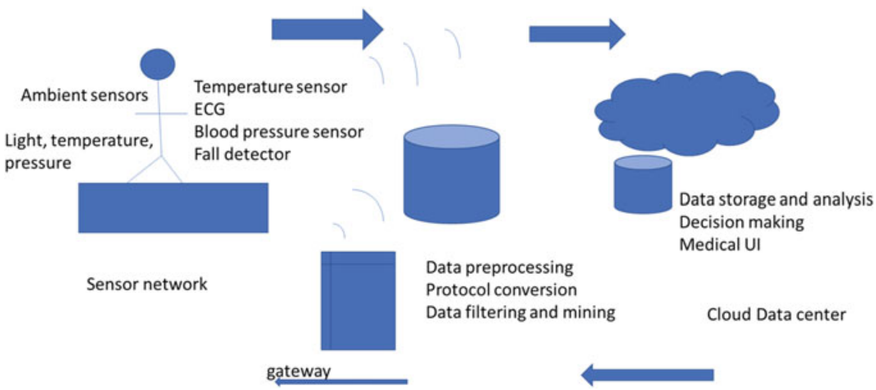

Fig. 1 Typical architecture of the healthcare system

different actors in the healthcare system. The vital health parameters can be accessed and considered by physicians, nurses, and even the family of the patient.

Health status prediction in IoT-based healthcare system can be either online or offline [24, 25]. The difference between online and offline methods is that in the offline method, the prediction is not done in a real-time manner.

Online health status prediction is based on continually monitoring health parameters and analyzing the result to predict the ongoing problem. Data analytic that is done in IoT-based healthcare solutions tries to detect or predict the abnormal behavior of the patient. The online data that are collected from the patient in the healthcare system can be further analyzed offline. The biosensors that are wearied by the patient are responsible for gathering health data. The other important features are age, sex, and other historical data about the health status of the patient. There are also another relevant data that are available with the help of IoT technology: the environmental status of the patient [26].

On the one hand, offline health status prediction, the health data, is gathered and analyzed offline to estimate the probability of specific disease. On the other hand, online health status prediction can help the patient with immediate feedback.

3 Typical IoT-Based Healthcare System

In a typical healthcare system, the monitored data are transferred to the remote using a cloud system or without it. We classify the works in this regard. In Sect. 3.1, the authors describe IoT-based healthcare system that uses cloud computing to increase the accuracy of health status detection and prediction. In Sect. 3.2, non-cloud-centric systems are explained.

3.1 Cloud-Centric IoT-Based Healthcare System

Cloud computing is quickly becoming a necessity in the medical field. It can be used as a media for shared data between different parties, and it can be also used as media for big data analysis.

Parvathy and Rajasekar design a system that monitors parameters such as temperature, heartbeat, and pressure and use it to predict the disease of the patient. Figure 2 shows the architecture of the proposed method by Parvathy and Rajasekar [27]. There is some predefined threshold for these sensors to indicate a special disease. For example, the blood pressure is measured, and the thresholds are predetermined. If the blood pressure goes beyond the value, there is an alarm to indicate it. If all the sensor value is within the predefined threshold, he is healthy. All the data if all the three parameters are sensed are between the threshold values, then the patient is said to be healthy. The data are stored in the cloud. The reported alarm is sent to the physician.

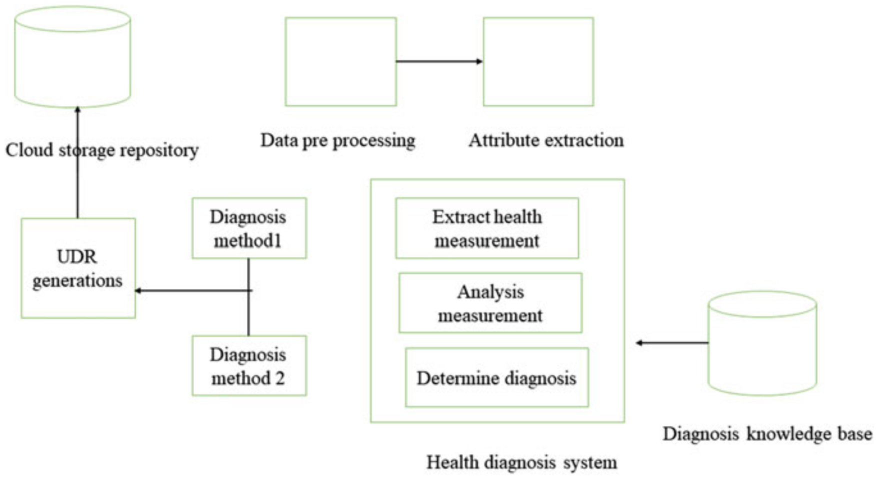

Fig. 2 Cloud subsystem

Pinto et al. [28] present a work to monitor the patient's vital parameter, and they trigger an alarm to notify the elderly people of possible risk. The effected range for communication is improved regarding related works. The work's name is WeCare. It consists of a wristband that acts as a gateway, collects wearable sensor data, and sends them to the remote host. They promote the everywhere part of the IoT concept so that the elderly people's quality of life improves. They propose that a single platform for all stakeholders consists of health services like e-prescribing [29]. Different healthcare applications are proposed in the cloud. The medical information can transfer easily. They propose a framework that transforms medical data. It gathers data from all subsystems. However, security and privacy are a concern.

Verma et al. propose a framework for monitoring the health status of the students [30]. They collect the environmental and body sensor data of 182 suspected students. They apply the decision tree and k-nearest algorithm [31] to analyze the data, and then the result is sent to the caretaker. In the student subsystem, the students register in the mobile application of the proposed system. Then, they fill the form related to health information. Then, the students wear some sensors like ECG/EEG and blood pressure. The data are transferred using a smartphone that acts as a gateway. The data are sent from the gateway to the cloud repository. The cloud subsystem is the subsystem that stores student health data. The data include temporal information. In the preprocessing phase, the dimension of the recorded data is reduced. In the next part, the oncoming event is classified based on the type of events like high temperature, glucose level, and blood pressure. The classification is done by the Bayesian belief network [32]. There are three data sets: student health sensor data, environmental sensor data, and historical data. Environmental sensors can detect temperature, air quality, and the existence of any toxic or noise. Behaviors like stress,

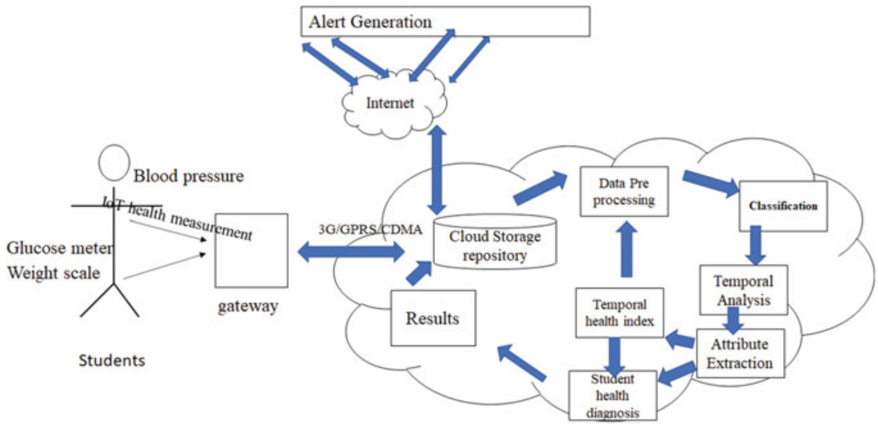

Fig. 3 IoT healthcare subsystems and processing parts

anxiety, and tiredness can be detected by biosensors. Motion can also detect some behavioral characteristics. Figure 3 shows the proposed subsystems and processing parts.

Verma et al. use the data set of 182 students in the range of 5-18 ages. Furthermore, they extract the data set from the data.opennepal.net/datasets. The waterborne disease and weight of each symptom of the mentioned diseases have been considered.

3.2 *Non-cloud-Centric IoT-Based Healthcare System*

The health status detection mechanism can be done by ECG signals [33]. They monitor ECG data online and use hidden Markov model [34] to anticipate the next patient location in case of emergency for finding the patients with cardiac problems. The result is also sent to the hospital database for future analysis [35, 36].

Gayathri et al. [37] detect abnormal health conditions. They deploy hierarchical Markovian logic networks. The assumption that is taken is that there are several different sensors deployed within the house. The goal of the study is obtaining the abnormal condition: (1) sensor's data; (2) the time of patient arrival; (3) the duration that a patient stays in a room; and (4) the possibility that patients do more than one activity at the same time. They deploy two learning approaches. The first method is used for activity detection and classification. The second method can extract the relevancy between different features. Thus, the abnormality in health status can be recognized. This solution has noticeable overhead.

Gope and Hwang propose a solution named BSN-Cared which is a secure body sensor network for monitoring the vital health parameter [38]. It is shown in Fig. 4.

Security is one of the concerns of the work. The wearable sensors that are used in this application are blood pressure, EMG, EEG, ECG, and motion sensors. The

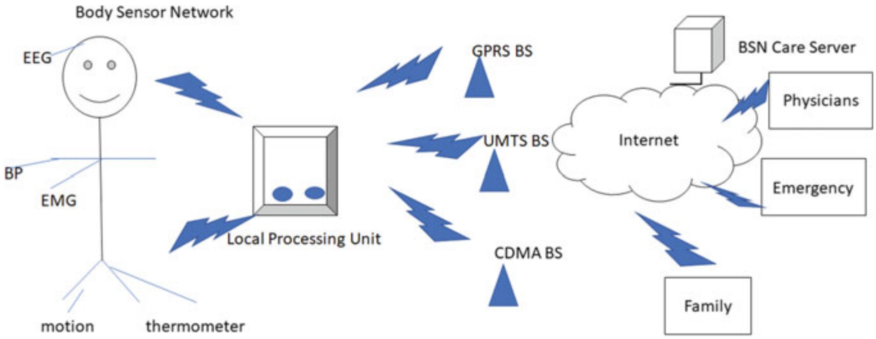

Fig. 4 IoT healthcare systems in BSN-Cared solution

collected data are transferred to the local processing unit which acts as a gateway. The communication facility is provided with GPRS or 3G. If any measured data reach beyond the normal threshold, the alarm rises. The abnormal data are also sent to the server. At the server, after analyzing the received data and all the related data at the database it either interacts with a local physician or informs the family members.

Numerous learning methods [41] can be applied in different parts of patient health status detection and prediction. Applying many different learning methods in the healthcare system can help us recognizing normal activity and knowing the relationship between different features of the environment and the normal behavior of the patient. Therefore, an un-normal pattern can be recognized. However, offline methods cannot predict the abnormal health status of patients or elderly people. Chiuchisan et al. propose an architecture for detecting the abnormal status of the patient at a remote server [39]. The device that is used is XBOX KinectTM. The environmental condition is measured by sensors.

4 IoT-Based Healthcare System with Edge Computing

The big problem with massive data analyzing and storage is that the healthcare system is sensitive to time as they must prepare the data within some restricted time. Transfer data from the monitored area to the centralized database and then from the centralized database to the cloud system. This takes time and decreases the response time. Fog computing has an important role in healthcare IoT systems. Research in this area is still in progress [40].

Nowadays, the use of cloud and edge computing [27] in the healthcare system is obvious. Edge computing is a distributed computing paradigm which brings computation and data storage closer to the location where it is needed, to improve response times and save bandwidth.

The use of fog computing [41, 42] can help to reduce the side effect of the mentioned concern [43]. The typical architecture of fog-based IoT is depicted in

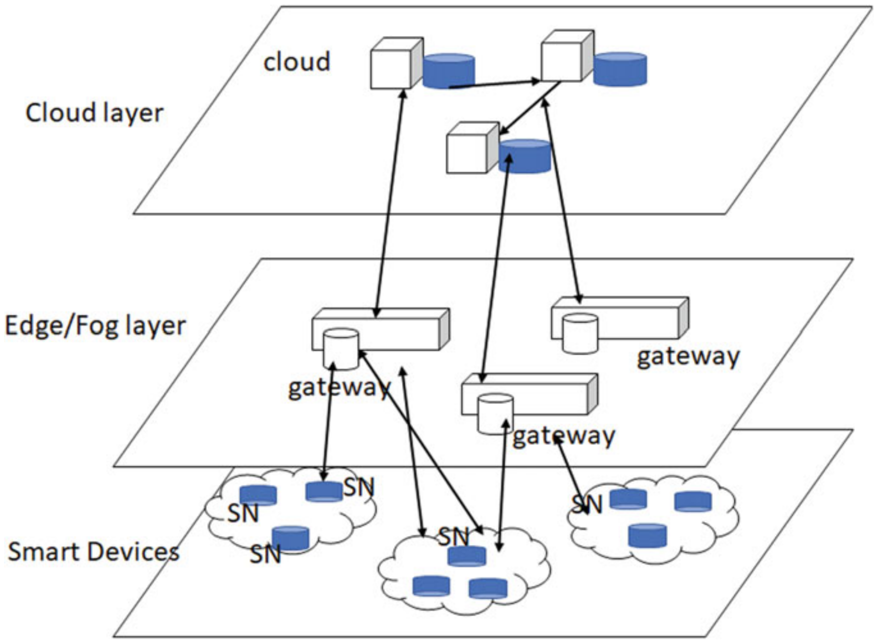

Fig. 5 General architecture of fog-based IoT

Fig. 5. Fog is a mediate layer between cloud and sensors that provides additional services that can help the system in computing some vital analysis in a nearer location compared to the cloud.

IoT along with cyber-physical systems [44] helps to develop a more capable healthcare system. They use a fog layer to provide the required services in the fog layer rather than the cloud layer.

In a typical healthcare system, the gateway is located between sensors and the Internet. It translates the protocols between two ends. It controls data transmission between sensors and the Internet. Rahmni et al. [43] implement gateway at the fog layer to provide some services like data mining, storage, and real-time processing. They use fog computing to handle the mobility of patients and thus provide a more power-consuming method. The gateways at the fog layer receive data from different sub-networks, perform protocol conversion, and provide other higher-level services such as data aggregation, filtering, and dimensionality reduction. The backend system at the cloud provides more analytics. Data warehousing is also done in the cloud. The smart gateway at the fog communicates directly with the sensor.

Bhatia et al. present an intelligent healthcare framework based on IoT to provide remote monitoring. They analyze real-time health conditions and predict health status. They construct an artificial neural network (ANN) model. They validate their work by experiments on five people. These different parameters of people are monitored for 14 days using numerous smart sensors. The results show it has a

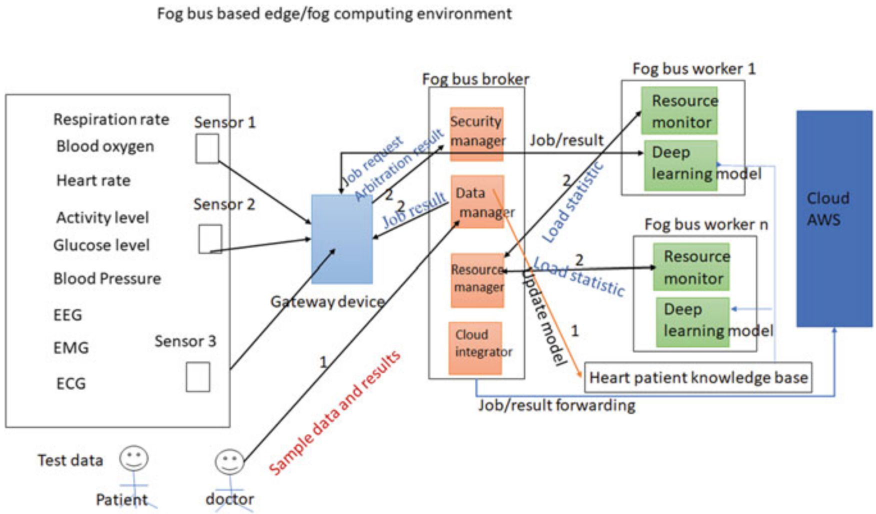

Fig. 6 Fog health architecture

better performance compared to similar research and is highly effective in delivering healthcare services during workouts [45].

HealthFog [46] provides a healthcare service at the fog so that the computation is done more efficiently by the time. The deep learning part is done in the fog to analyze the collected data from IoT devices. HealthFog architecture is shown in Fig. 6.

The Resource Manager consists of two parts. Workload manager holds the job queue for preprocessing. The arbitration module provides either fog or cloud for task processing. This module is located in the broker node and decides the node that must forward the data. The worker node is responsible to do a task that is assigned by the broker. The broker node receives all the job request. The gateway can be a mobile phone or tablet. Data filtering and preprocessing are done to reduce the dimension of the collected data. The ensembling module applies the voting method to select the most probable prediction.

There is also another solution to increasing the accuracy of health status prediction. In this approach, activity recognition methods [47–49] are applied to determine the health status of the people/elderly people more accurately.

The philosophy behind this method is that the abnormal activity for the duration can be a sign of a problem [50–52]. However, as accurately predicting the health status of a patient can save a life, the accuracy of the applied method is so important and the research in this area is not enough. Another issue in the activity recognition-based method is that the accuracy of the method decreases dramatically when it is deployed in a real environment rather than a testing environment [53].

Kelly et al. [50] deploy motion sensors, location sensors, and sound sensors to predict the health status of the patient more accurately. They apply the support vector machine [54] and can extract 10 different health metrics. Big data analysis is a concern in activity recognition based on healthcare systems.

The previous work of the author presented in [7] introduced an approach for online prediction of the health status of patients. The environment is divided into equal-sized cells. At the center of each cell, a static node is positioned. The static node is a sensor that sends the time of arrival of the patient, the duration of staying within a cell, and the ECG data of the patient to the gateway. The ECG data are sent periodically. This work is done for every patient within the indoor environment. For one month, the data is collected. Then at the gateway, the HSMM learning method is used to train the model. HSMM is a hidden semi-Markovian model [55] which takes into consideration the duration of staying within a cell. After constructing the model, it splits around the area and each static node at the center of each cell receives a portion of the model that is related to itself. The communication between static nodes is done with the special routing path. A tree is constructed with all static nodes in which the static nodes at the center of each cell are leaves of the tree. A mobile node will communicate with the gateway via leaf nodes. Since people in elderly households have an almost predefined daily routine, they recognize activities in each cell implicitly without using any biological, environmental sensors to record the patient's physical state, objects, or environmental conditions. The proposed method constructs a distributed online prediction of mobile node data in IoT healthcare applications. Existing approaches that detect a patient's health status using activity recognition methods are not cost-effective, due to their need for using lots of body. The results show the effectiveness, using time of arrival within a cell, ECG signal, duration, and location in increasing the accuracy of our proposed method.

5 Open Research and Challenges

Real-time health status prediction and monitoring face many challenges. These include power, response time, and accuracy of the prediction method. The computation that must be done to increase the accuracy of prediction takes time and needs the power that is in contrast to IoT-based healthcare system in which the devices have low power and the immediate response to measured data has a critical role to save the life of the people. Thus, nowadays edge computing and fog computing are in a new focus. However, the efficiency and power consumption of the healthcare system are still challenging.

The one concern of the IoT healthcare system is the continuous collection of data from the sensors and analyzing at the same time. It is a challenging task as the limitation that exists in both storage and communication media. As every patient has its characteristics and health data, in an environment with n patients, we have to consider enormous data storage, computation, and communication capacity. The other concern is maintaining the health status model update. It arises a question that what is the best time to update a model. As it requires time and cost to the so, finding an optimized time is a necessity.

Cloud computing is quickly becoming a necessity in the medical field. It can be used as a media for shared data between different parties but also as media for big data analysis. Edge computing is a distributed computing paradigm which brings computation and data storage closer to the location where it is needed, to improve response times and save bandwidth. Fog is a mediate layer between cloud and sensors that provides additional services that can help the system in computing some vital analysis in a nearer location compared to the cloud. The use of serverless computing in healthcare system is new in this area and can decrease the cost of the whole system. There are still some challenges like real-time prediction, security, and privacy in implementation of this technology in IoT-based healthcare system.

6 Conclusion

In this chapter, we consider health status prediction in IoT-based healthcare systems. We first describe the basic concept of IoT-based healthcare systems. Then, we consider health status prediction and the overall impact of health status prediction in saving the life of people. We describe different technologies in IoT-based healthcare system including edge and fog computing. Cloud computing is quickly becoming a necessity in the medical field. It can be used as a media for shared data between different parties, and it can also used as media for big data analysis. Cloud computing and edge computing are employed to communicate between different healthcare subsystems. Edge computing is a distributed computing paradigm which brings computation and data storage closer to the location where it is needed, to improve response times and save bandwidth. Edge computing-based healthcare systems are more efficient as the computing is done in nearer places to patients. Thus, the health status prediction is done in real time which is very important in healthcare systems. In other words, IoT-based healthcare systems apply fog, edge computing [13], and serverless computing to predict the health status of the patients more accurately and efficiently. Future research includes focusing in serverless computing in patient monitoring system to increase the efficiency of the system.

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IoMT-Based Wearable Body Sensors Network Healthcare Monitoring System

Emmanuel Abidemi Adeniyi, Roseline Oluwaseun Ogundokun, and Joseph Bamidele Awotunde

1 Introduction

The Internet of Things (IoT) is described as a set of recognizable items or nodes that can communicate through wired or wireless networks [1, 2]. IoT is the world's third wave of information after computer, Internet, and mobile communication technologies were introduced [3–5]. The IoT-based cloud has more than 26 billion connected devices and is estimated to produce global economic value revenues of $1.9 trillion by 2020 [6–8]. Moreover, 40% of IoT-related technology is health related, more than any other category, representing a market of $117 billion [9–11].

IoT tools in the healthcare sector such as sensors may have various applications like heart rate sensors, blood glucose monitoring, and endoscopic capsules [12–14]. The combination of sensors, actuators, and as well as other mobile technology equipment will transform the medical industry's functioning [15, 16]. Such systems, known as the Internet of Medical Things (IoMT), are a connected system of healthcare smart devices that receive information subsequently offered by web communications systems to healthcare IT systems [17–19]. Currently, 3.7 million medical equipment is already in use and linked to and monitored by different parts of the body to notify medical decisions [20, 21].

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_6

The IoMTs are an important component of wearable healthcare systems like bio-systems, recovery robotics, and identification of events [22, 23]. The IoMTs is the core of mobile medical systems by combining implantable/wearable nodes to acquire bio-signals such as electromyogram (EMG) and electrocardiogram (ECG) [24–26]. IoMTs enable access to medical services to monitor patients at any time in any location. The IoMTs have begun to appear as the center of applications for tele-health supervision to improve the severe scarcity of resources available. The IoMT is an assortment of medical systems and platforms that connect through Internet-based computer systems to healthcare IT systems. Medical equipment connected with wireless communication that permits machine-to-machine connectivity, which is IoMT's principle.

These IoMT devices connect to cloud infrastructures such as Google Cloud Computing, Microsoft Azure Cloud, Amazon Web Services, or any other custom web services capturing storage and analytics information. Furthermore, IoMT services include remote medical observation of persons with chronic or long-term situations. These systems can monitor patient treatment instructions and track the position of patients who are placed on wearable healthcare tools in hospitals and clinics. The collected health information can be delivered to their care provider. Medical devices that can be integrated or deployed as IoMT technology are infusion pumps that attach to analytical dashboards and hospital beds with sensors that measure vital signs of patients. The IoMT receives its maximum capabilities through the use of objects, i.e., "Smart" objects, which use multiple sensors and actuators fully prepared to learn in their context, and through the use of embedded communication infrastructure to communicate with any possible alternatives.

Technological developments of low-cost, intelligent, small, and portable medical sensor nodes have been approved in wireless transmission and wireless sensor networks (WSN) to position themselves perfectly on the human psyche [27]. This helps to build a wireless body area (WBAN) network to supervise numerous important chronic physical illnesses for a long-term provide user and medical staff with real-time feedback, thus promising to revolutionize health monitoring [27]. WSN applications are considered as one of the major fields of research for improving quality of life in the computer science and healthcare applications industries [28].

Body sensor node system will help users by providing public healthcare services such as health tracking, memory improvement, home appliance control, access to health data, and emergency communication [29]. Constant monitoring with wearable devices will significantly raise the early diagnosis of a case of emergency conditions and diseases in patients at risk, as well as provide a wide range of health care for people with different levels of cognitive and emotional illnesses. These systems will benefit not just the elderly and chronically ill patients, but also the households where both parents are working to provide their babies and children with good quality care services. This chapter, therefore, proposes an architecture of an intelligent IoMT healthcare system for monitoring patients with diabetes mellitus using a WBSN.

The main contributions of this chapter are (1) the implanted of WBSN in the IoMT-based platform for healthcare monitoring system, (2) the use of WBSN in the IoMT-based platform to monitor a patient with diabetes mellitus, and (3) the use of hybrid sensors for the proposed system. The result of the chapter shows that a Systolic Blood Pressure (SBP) < 110 is normal and $\geq$160 is in stage II diabetes; Diastolic Blood Pressure (DBP) < 70 is normal and $\geq$100 is in stage II; Plasma Glucose Concentration (PGC) $\leq$ 71–100 is normal and $\geq$122 is in stage I; (INS) 2-h Serum Insulin $\leq$ 97–138 is normal and $\geq$191 is in stage II; and Body Mass Index (BMI) $\leq$30 is normal and $\geq$50 is in stage III. The length of days of diabetes is a relevant determinant risk factors of diabetes mellitus.

The rest of this chapter is organized as follows: Sect. 2 discusses the IoMT. Section 3 presents an extensive discussion on wearable body sensors networks in health care. Section 4 highlights and discusses the sensor devices on the Internet of Medical Things. Section 5 presents the IoMT-based wearable body sensors network framework for the healthcare monitoring system. Section 6 presents a practical case of the diabetes IoMT-based WBSN monitoring system. Section 7 explains the results and Sect. 8 presents the discussion and future research directions. Finally, Sect. 9 concludes the chapter and discusses future works for the realization of efficient uses of IoMT-based WBSN in healthcare monitoring systems.

2 The Internet of Medical Things

In developing countries, the healthcare sector is shifting rapidly as life expectancy grew dramatically during the 1990s [30]. Infectious illnesses are also placing increasing pressure on healthcare systems in these countries [31]. The life expectancy in advanced nations during the twentieth century has been raised by about 30 years. As a result, the number of elderly people has risen rapidly [30]. Also, chronic disease proliferation has put pressure on healthcare systems in other countries due to a lack of funding [31]. Increasing infectious illnesses and aging populations present significant challenges, as health systems have to deal with a multitude of ailments and treatment options, but similarly a rising patient number. To avoid overloading health infrastructure and reducing the costs of healthcare, successful approaches have been shown in-house telemedicine services [32].

Telemedicine platforms are extremely diversified and typically designed to respond to a single therapeutic purpose, like mobile cardiac monitoring and stroke recovery [33]. This attribute of telehealth systems makes them cost effective and overloading health systems, but reflects a weakness as patient numbers and disease variety increase. The IoMT can handle the need for stronger genericity and reliability. Admittedly, the IoMT integrates both the efficiency and security of traditional medical equipment and the traditional capacity for dynamics, genericity, and scalability of IoT. It devises the potential to fix the aging problem and terminal illnesses by managing various sensors deployed for millions of patients and as well as being broad enough to deal with various illnesses requiring precise diverse checking and action specifications.

Additionally, IoMT offers a solution to challenges like the movement of patients. Therefore, it is possible to make an omnipresent evaluation of patients in their

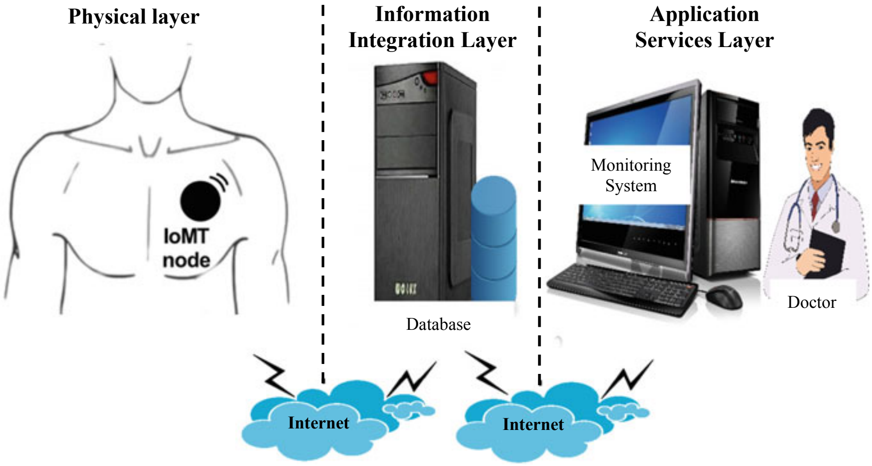

Fig. 1 Structure of IoMT

everyday routines, as opposed to telemedicine services which are strongly focused on home treatment. Given the challenging existence of these concerns, the way we achieve medical services is evolving with new technology innovations to requesting health services in advanced countries. The development of computers and other devices, along with the benefits in computing capabilities in these devices, promotes the implementation of the IoMT and propose clarifications to the requirements of both our elderly people and chronic illness patients. The IoMT is the connectivity not only of multiple medical types of equipment but likewise of devices and health professionals like hospitals, medical experts, or private enterprises.

The IoMT displays an essential role in improving the accuracy, consistency, and performance of electronic equipment in the healthcare sector. To improve the health of patients [34], the IoMT describes the interconnection of medical-grade devices allowed for communication and their incorporation into broader health networks. The introduction of the IoMT is primarily due to the increased usage and advancement of coupled and dispersed medical equipment which brings both enticing possible applications and problems that occurred [35]. Since personal medical devices also come as wearable devices, the chapter focuses on wearable medical devices being incorporated into the IoMT. Figure 1 presents the structure of IoMT.

3 The Wearable Body Sensors Network in Health Care

WSN has transformed the power to change our lifestyle with abundant technologies in areas of health care, entertainment, transportation, retail, business, and emergency services control in addition to many other areas. The integration of wireless sensors and sensor networks with simulation and intelligent systems research has developed an interdisciplinary definition of ambient intelligence to address the obstacles we face in our everyday lives [36].

The WSNs with smart sensor nodes have become a substantial technology enabling a wide spectrum of uses. New technologies in the incorporation and mass production of single-chip sensing devices, computer chips, and radio interfaces have allowed WSN to be appropriate for several applications [28, 37, 38]. They could be used, for instance, for emergency preparedness, factory equipment, surveillance systems, seismic surveillance, environmental control, agricultural practices, and health monitoring. Among the most hopeful usage of WSN is monitoring healthcare [39, 40].

A sensor network is a network of several nodes furnished through a sensor module, a memory chip, a microprocessor, a wireless connectivity interface, and a multi-hop power source [41, 42]. With routing responsibilities, the nodes in the same proximity can interact with one another [42]. Opposing to the popular sensor nodes that are meticulously crafted and installed in the defined locations, WSNs could install an ad hoc, making them resilient, fault-tolerant, and increasing coverage area [43, 44]. They can be used widely to control and track patient conditions in both towns and cities using an internal network. Therefore, these methods can minimize pressure and tension on healthcare professionals, eliminating medical faults, reducing workload and medical staff productivity, reducing long-term healthcare costs, and enhancing patient satisfaction [27, 45, 46].

These inaccuracies happen as a result of a lack of comprehensive and accurate information at the time and place required, leading to an erroneous treatment and issues with particular medication [46, 47]. The risk of death can be lowered if appropriate measures are provided to patients at the proper moment [27, 48]. To ensure the safety of patients and to save lives, hospital personnel must have the right to information about patients at the right and within a short period. Therefore, it is necessary to provide a safe and low transmission latency for patients with life-threatening diseases like diabetes mellitus, heart diseases, and blood pressure. To build a cluster WBAN, sensor networks can be well-positioned on the human body and, therefore, used to retrieve symptoms from patients [49, 50].

For effective and convenient transmitting of data between WBAN and personal server, a battery cell sensor network is required, and their energy consumption during transmission should be relatively low. The examples of IoT devices using for communication technology are smartphones, which use the Internet, General Packet Radio Service (GPRS), 2G–5G technology. These technologies enable us to keep patients, physicians, and caregivers informed while also setting a pattern and identifying health variations. This is called biomedical sensor wireless networks (BWBSN) when applied to biomedical technology [51, 52]. The WBSN enables low-power, remotely operated, smart pervasive sensor nodes to be embedded to monitor body systems and physical vicinity. Every node will sense, monitor, and then forward information to the Super Sensor. The benefits of wearable sensors are shown in Fig. 2.

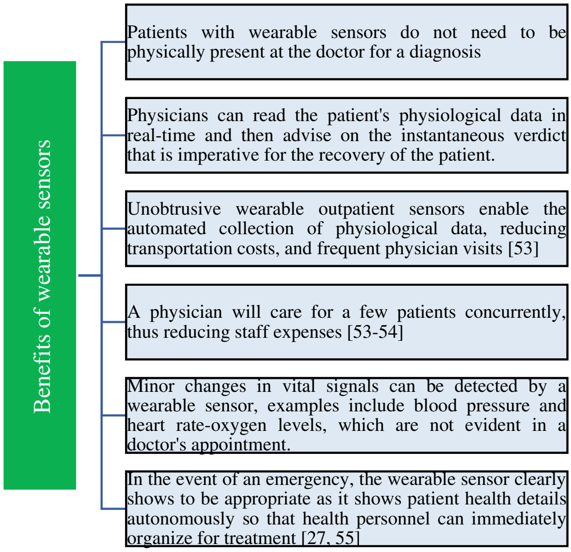

Fig. 2 The benefits of wearable sensors

4 Sensor Devices on Internet F Medical Things

Billions of smart devices and applications, such as WSNs, are not expected to be segregated but linked to and incorporated with communications networks in future IoT [56]. To manage these sensor devices well, systems also need to be designed to operate properly by allowing system management organizations to track and control systems remotely without the need for substantial resources.

The IoMT is known as a network that comprises of collecting medical devices and sensors that are intimately connected via digital technologies. Furthermore, IoMT uses embedded sensors, cameras, thermometers, air quality sensors, ECG/EEG/EMG sensors, pressure gauge, gyroscope sensors, sensors for saturation of blood oxygen, temperature, and humidity sensors, heart rate, and respiratory sensors to monitor and supervise the health of the patient continuously. The IoMT senses the health status of the patients and then transfers the clinical data to doctors and caregivers using remote cloud data centers [18].

Patient information such as body temperature, blood pressure, ECG pulse, heart rate, blood oxygen saturation levels (SpO2) can be obtained by a wearable sensor attached to the patient body. One of the critical layers in IoMT architecture is the connectivity of sensors and the network. This component is an essential part of the IoT ecological system which offers access to other layers in the network. IoMT environment sensors serve as frontend. These devices may be closely relevant to IoT networks whenever the transformation and processing of the signal have been identified. Nevertheless, not all sensors are the same, and nowadays, there are several types available in the market. For instance, two to three days of continual physicochemical measures based on sensor devices were monitored by scholars and used to collect related parameters to update specific healthcare records [28, 57]. Sensors allowed the collection of personalized health data and behaviors of patients and these data can be transferred to the cloud for further analysis.

Healthcare services focused on smartphones have a clear propensity to have a cost-effective long-term healthcare management alternative [58]. These systems can enable healthcare physicians to monitor their patients' health status remotely without invading into their daily routines [59]. Smartphones also have numerous embedded sensors including an image sensor, an accelerometer, an ambient light sensor, a GPS sensor, a gyroscope, a microphone, and a fingerprint [60]. These sensors help to evaluate numerous patients' health parameters including heart rate, variability in heart rate, respiratory rate, body glucose, and blood pressure only to consider a few. This makes the communication device a continuous and long-term monitoring tool for health care. Figure 3 presents some of the sensors used in IoMT for information gathering. These sensors allow health personnel including a doctor to monitor the progress and health parameters of the patient in real time.

There is a growing amount of wearable technology (smartphones, tablets, and watches) that must be taken into account when developing an IoMT-based human monitoring application. Smart-watches can form a wireless network called the WBAN, with the primary aim of obtaining human body physiological data. At this moment, when formulating connectivity between WSN and wearable devices, a

Fig. 3 Sensor devices for collection data on IoMT

significant problem appears when varying standards for various system components need to work in this same environment.

IoMT offers the chance for healthcare scientific advancements to continue to flourish and also enables the solution to stay abreast of time [60, 61]. Moreover, IoMT provides a huge amount of data, often called big data, which cannot be analyzed through conventional data processing algorithms and applications. By constructively researching and capturing vast quantities of medical data, IoMT can increase decision making and early diagnosis of diseases.

5 IoMT-Based Wearable Body Sensors Network Framework for Healthcare Monitoring System

IoMT-based WBSN Healthcare Monitoring System Architecture is a complex task, and a variety of systems were examined. Data collection and combination from multiple IoMT devices is one of the major challenges facing IoMT's realization in designing smart customized healthcare systems. In most cases, data is not always available in real time, so there is a challenge in evaluating or integrating a wide range of data since IoT devices obtain dynamic and complex data on medical assessment, tracking, treatment plan, and prediction in health care. The aggregation of data from specific sensor data sources is a major problem that needs to be addressed critically.

Therefore, it would be encouraging to investigate which of the IoT sensors enhances the efficiency of the intelligent systems with a collection of biomarkers of multiple diseases. So it would be crucial to investigate whether any other background data existed which could improve the efficiency of the model. Besides, further studies are required to determine the quality of the attributes selected from each biomarker. Other relevant matters in IoMT implementation for monitoring of patients, evaluation, treatment plan, and prediction is the need to design a system that can accurately switch between cloud and local classification methods with minimal processing time to ensure real-time and up-to-date provision for the patient.

This chapter proposes the framework for the IoMT-based wearable body sensors network healthcare monitoring system (IoMTWS), which applies a range of wearable sensors interconnected to track a patient's health condition. The use of body temperature and pulse, for instance, helps to collect physiological signals. The sensor data collected from these wearable sensors will be transferred directly to the cloud server due to the small computing power of the sensor nodes and the storage, as well as to avoid the use of a smartphone as a processing device.

The design process of the IoMT-based Network Healthcare Monitoring System for wearable body sensors is depicted in Fig. 4. The IoMTWS comprises three major elements, the IoMTWS body area network (I-BAN), the IoMTWS server (I-Cloud), and the IoMTWS users. The I-BAN constitutes any sensing instruments, including sensors such as body temperature, cardiovascular disease sensor, pulse sensors, and blood pressure sensor. With the advent of cloud-based services, the IoMTWS BAN

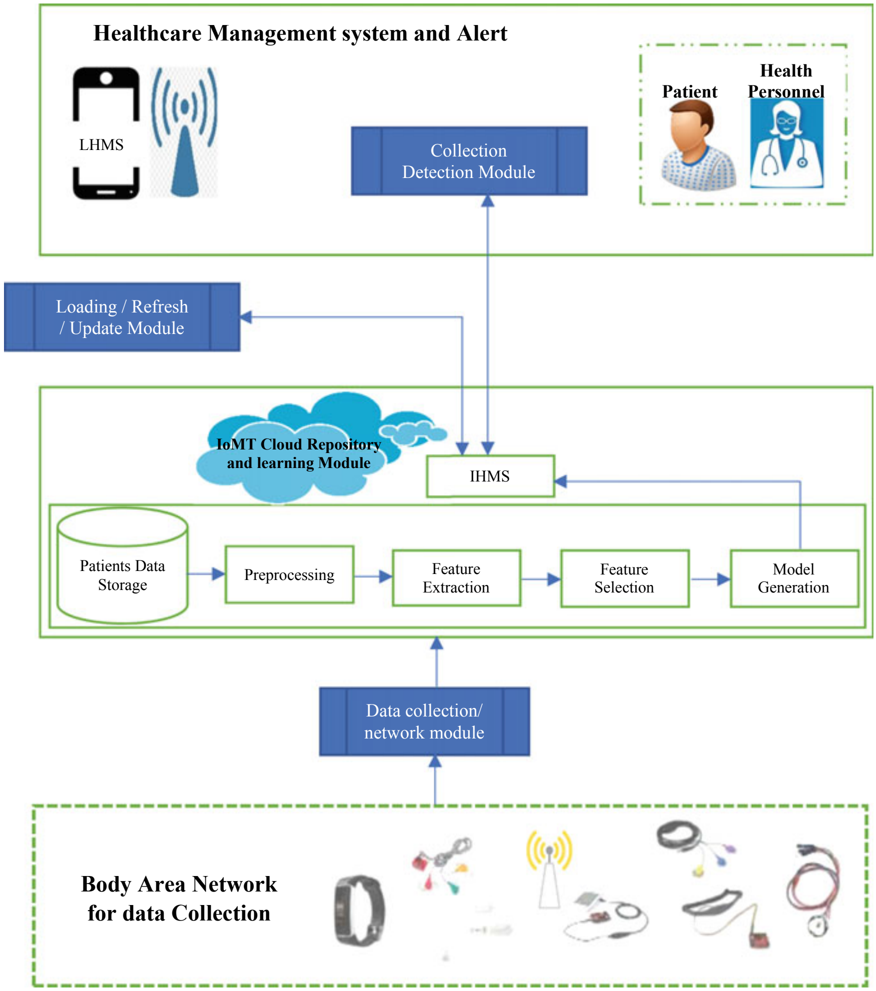

Fig. 4 Proposed IoMT-based WBSN framework for healthcare monitoring system

information could be easily and securely stored and processed on the Internet. With IoMTWS cloud, several implementations like disease identification, data collection, and storage, verification, and data visual analytics can be implemented.

There is a growing number of wearable technology that must be considered in designing an IoMT scenario-based human monitoring program. Wearable devices can form a wireless connection called WBAN, the primary aim of which is to collect physiological parameters from the body of the patient. At this level, a significant element between WSN and wearable devices are different requirements for different system components.

This chapter proposes a method that aims to address the aforementioned research issues for the management system in health care. The proposed framework consists of five modules: data collection/network module, cloud-based data repository and learning module, model update module, a connection detection module, and a module for review, tracking, prediction/diagnosis, and alert management. The first module operates as WBAN, which consists of sensors, communication, and networking as the module for data capture. The data from this module is transmitted for modeling into the cloud data repository.

On the cloud layer, an adequately equipped and validated IoMT-based Personalized Healthcare Model (IPHM) could be used to test, track, predict, or evaluate any patient whenever a connection has been established. This system also includes an upgrade module, which updates the Local Personalized Healthcare Model (LPHM) on the mobile phone automatically. In case of Internet access interruption to the IPHM, the LPHM interface acts as the local intelligent device. The system includes a link detection module to accomplish this switching, which automatically identifies whether the user's smartphone is connected to the network or not. This connection ensures a simple, robust, and accurate cloud-based architecture for patient examination, tracking, forecasting, and treatment plan.

6 Practical Case of Diabetes IoMT-Based WBSN Monitoring System

Diabetes mellitus (DM) has been one of modern society's chronic and debilitating diseases and describes not just a medical condition but also a socioeconomic issue, thus the immediate need to help stop pandemic expansion in society. Diabetes mellitus (DM) is increasingly becoming a major epidemic, compiling the severity of DM, negatively impacting both genetic and environmental factors and a complicated disease [62, 63]. The World Health Organization (WHO) estimated that by 2030 some 350 million individuals globally will suffer from diabetes [64, 65]. The four cases of diseases are pre-diabetes, Gestational, type 1, and type 2 diabetes mellitus. Insulin-dependent diabetes is type 1 [66, 63] unless developed by the insulin hormone. Non-insulin-dependency diabetes is type 2, where the brain cannot use insulin from the body [66]. Diabetes is called gestational diabetes during pregnancy [67]. Pre-diabetes occurs when blood glucose levels are elevated but not as high as diabetes for diagnosis [68, 63].

Diabetes mellitus is responsible for multiple diseases such as kidney failure, nerve damage, artery damage, blood vessel damage, blindness, and heart disease [69]. Furthermore, IoMT based has been described as among the key components in the management of diabetes disease, risk assessment, patient tracking, and prediction in the medical field. Type 1 diabetes accounts for 5–10% of all diagnosed diabetes cases. The category is formerly referred to as insulin-dependent diabetes mellitus (IDDM). Compared to type 2 diabetes, risk factors are not well distinguished. The most likely cause of type 1 diabetes is hereditary and hormonal factors. Type 2 diabetes is responsible for about 90% of patient diabetes, making it the most common diabetes among all diabetes types, and is an earlier adult-onset diabetes called non-insulin-dependent diabetes mellitus (NIDDM). Old age, family history, history of gestational diabetes, impaired tolerance of glucose, obesity, physical inactivity, and ethnicity/race are the type 2 diabetes risk factor.

Gestational diabetes in all pregnant patients is responsible for 2–5%. It occurs during pregnancies and normally vanishes after patient delivery. Pregnant women have enough insulin; this effect is called insulin resistance, partly due to the variation of other hormones produced in the placenta. Kidney disease development can be diabetes aids, increases the case of heart disease, damage to the blood vessels, blindness, and nerve damage. The precise prevalence of diabetes and the analysis of its data can help with the issue of diabetes classification. In gestational diabetes, the body is not using insulin properly, which is insulin resistance associated with absolute insulin deficiency. Table 1 shows the ratings of the data for the proposed system for monitoring and diagnoses of diabetes mellitus. Table 1 shown the rating indicators for DM by physicians [63].

Therefore, both IoMT-based and WBSN is seriously needed to develop effective and useful surveillance and prediction method for DM to assist in early detection and diagnosis of DM to promote prompt blood glucose regulation which will lead to improved health outcomes for those who may develop DM and DM patients. This section presents the experimental findings of the preliminary investigation of

Table 1 Rating of indicators for DM by physicians

Input field	Range				Fuzzy set
	1st physician	2nd physician	3rd physician	4th physician	
1. Glucose	≤71–110	≤90	≤120	≤121	Low(L)
	94–120	95–130	97–138	96–145	Medium (M)
	≥121	≥122	≥124	≥125	High (H)
2. INS	≤15–80	≤15–78	≤20–86	≤17–87	Low (L)
	15–100	20–150	17–90	15–100	Medium (M)
	≥89–194	≥95–193	≥192	≥194	High (H)
3. BMI	≤24	≤27	≤33	≤30	Low (L)
	24	35	39	40	Medium (M)
	≥33	≥35	≥37	≥40	High (H)
4. DPF	≤0	≤0.2	≤0.3	≤0.4	Low (L)
	0.2	0.3	0.4	0.6	Medium (M)
	≥0.4	≥0.6	≥0.7	≥0.4	High (H)
5. Age	≤30	≤29	≤38	≤35	Young (Y)
	33	40	42	43	Mid
	≥45–55	≥47–54	≥50	≥58	Old (O)

the proposed WBSN Platform for Healthcare Monitoring Program based on IoMT. For this chapter, an inter-digital sensor-based sensor network was used to create a monitoring system for diabetic neuropathy patients. To monitor the tremor in a different part of the body, embedded sensors in clothing have been identified as a unique method thus helps in the day-to-day analysis of the activities of patients and monitor patients' progress and thereby result in early detection diabetic neuropathy variations.

Health wearable systems are relevant to patient tracking in the routine operation of preventive medicine and safety promotion. Both systems that use the network layer and intelligent networks can be integrated to enhance individual medical devices. The metabolic symptoms sets describe the condition that exceeds standard values. The most metabolic symptoms are three of the five factors, obesity, cholesterol, glucose, blood pressure, and triglycerides, thus can result in multiple health issues, like cardiovascular disease and stroke. For type 2 diabetes, the most risk factors are age, obesity, alcohol consumption, hereditary disease, and gender-sensitive, or illness known to the patient [70].

Based on big data on the cloud, the information given by an intelligent sensor is much more precise and detailed. The proposed system combined two sensors and fused various sensors to enhanced monitoring and prediction of the physical phenomenon, hence increasing the measurement accuracy when compared with using a single sensor. The convergence is described as "incorporating information from other sources to develop unified data relevant and comprehensive about an individual" [71]. A wired or radio can be used to communicate with an intelligent sensor and adjust their parameters to verify the accuracy of the measurements.

The system composed of a pressure sensor network and a microsystem that involves an acquisition block, a storage block, and a block for data transfer. The two subprocesses are attached via a 9-wire bus to one another. The micro-device is part of a belt that can be connected to the waist. From the pressure sensor network, the power is provided from a 9 V battery connected to the device for data collection and to pass data from the internal memory to the computer. The experiments were conducted using the R data analytics tool. The system has a random-access memory of 8 GB and 2.90 GHz Intel Core i5 with both CPU and GPU support. The operating system is Windows 10 Pro 32-bit.

7 Results

Figure 5 and Table 2 display the calculated findings within the context of blood pressure, blood glucose, body mass index (BMI), and waist circumference measured values. Consequently, apart from high blood pressure and diabetes, obesity was listed as another high-risk factor of high blood pressure, diabetes, and hypertension as it symptoms can leads to any of these diseases [70].

Blood vessel circulation can be disrupted due to high blood glucose, thus leading to pain, and lack of awareness in the blood vessels. Mild bruises in diabetic patients

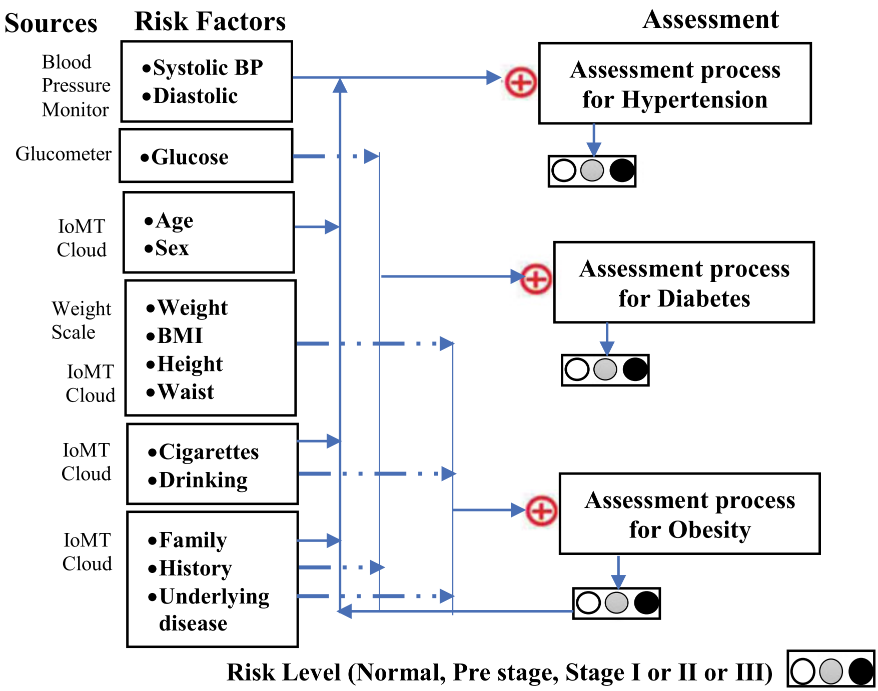

Fig. 5 Risk factors for diabetes, obesity and hypertension

Table 2 Classification of blood pressure, diabetes, and obesity

Risk factors		Normal	Pre-stage	Stage I	Stage II	Stage III
Blood pressure	SBP	<110	110–138	139–160	≥160	
	DBP	<70	70–89	90–99	≥100	
Glucose	PGC	≤71–100	100–121	≥122		
	INS	≤97–138	138–190	≥191		
BMI		≤30	30–39.9	40–44.9	45.0–49.9	≥50
Waist circumference		≤40, ≤30	>40, >30			

on foot could, therefore, become more serious issues when they are not properly treated in time [72, 73]. About 15% of diabetes cases resulted in diabetic foot and the side effect can endanger patient life [74]. The presence of diabetes in a body reduces the blood flow to the lower limbs, hence triggers an infection present in the patient body and easily escape control, thus has severe consequences that could lead to an ulcer, if untreated result to the amputation of the affected limb.

Diabetes length is a relevant determinant of diabetes risk factors. Diabetes patients of over 15 years of age feel to a much greater degree than their standard of living has been compromised over the last month by the need to follow the physician’s recommended care, dietary limitations on disease control, lack of blood glucose regulation, blood sugar monitoring and the effect on their vision issues. Nonetheless, patients with a relatively short and medium diabetes period (below 5 years or between 5 and 10 years after diagnosis) appear to be substantially more comfortable with the time needed to control diabetes.

8 Discussion and Future Research Directions

The basic concepts of IoMT-based and wearable body sensors network applications in the field of healthcare monitoring systems have been elaborately discussed in this chapter. The use of IoT devices in health systems, which are linked to the IoMT, is a relatively new and rapidly growing trend in health-related areas. From the broad range of research disciplines related to the implementation of IoMT technologies and wearable body sensors network applications in many medical case studies, it has been identified that IoMT and wearable body sensors network have offered a large number of new frontiers for generating, developing, analyzing, and managing large amounts of data frequency, particularly online and other, In this regard, IoMT and wearable body sensors network technology, as a common method to managing a large volume of health care data, has provided convenience from the perspective of personalized e-Healthcare.

In this chapter, an IoMT-based and wearable body sensors network architecture for Healthcare Monitoring System was proposed to answer some of the research questions highlighted in the chapter. The structure for the Healthcare Management Program of Mellitus Diabetes has been introduced for both the IoMT-based architecture and WBSN. Using the system, appropriate patient-related data are collected from sensors and analyzed, including the frequently changing health parameters.

The results show that the proposed IoMT-based and WBSN platform helps track and spread chronic diseases such as diabetes mellitus. For future research purposes, it should be noted that progress has been recorded in the study on the healthcare monitoring system in customized e-healthcare, but it is necessary to address a series of research questions and operational problems. In previous studies, various challenges concerning information safety and confidentiality, mobility control, and applications are identified during design processes. Thus, there is a need to concentrate on such challenges, particularly as they relate to IoMT and prediction, diagnosis, exams, and monitoring of disease. In this context, an intelligent security model should be thoroughly studied to minimize the risks identified.

Although different IoMT applications are widely available online, they are due to many deficiencies including lack of confidentiality and protection, reliability, efficiency, and appropriateness. Addressing the issue of load balancing and spreading knowledge through the cloud servers is of significant concern for future study. More effective security algorithms such as DNA encryption, fully homomorphic encryption, and decryption on the cloud need to be implemented just to mention a few.

Data privacy and security are challenging objectives in IoMT-based healthcare system monitoring [75]. Majorly because cloud's recorded healthcare data may be subject to different types of security risks, like connecting attacks and illegal users. Machine learning techniques should be further incorporated in a similar perspective to solve the issue referring to diverse and ever-evolving sensory inputs. Furthermore, it is often difficult to compare or connect data varieties from numerous sensor devices since sensors produce complex and heterogeneous data on clinical tests, tracking, and health care. It will thus be important to decide which one of the IoMT sensor data performs better for a collection of biomarkers, in order to obtain a better diagnostic result.

9 Conclusion

The proposed system is non-invasive, flexible, cost effective, and the framework empowers users to enhance monitoring of health-related signs and symptoms, vulnerabilities, and reduces hospital costs and expenses by recording, gathering, and sharing all-encompass health information on IoMT cloud platform effectively, continuously, and productively. The results show that the length of diabetes in a patient is very relevant and good determinant risk factors, also all the risk factors of obesity are related to diabetes risk factors; therefore, obesity is an important illness of diabetes mellitus. Furthermore, the results reveal that glucose, INS, BMI, and DGC are high-risk factors of diabetes. The framework can be used for monitoring other diseases using sensors that are related to that illness and well equipped with features that can help doctors to examine their patients anytime and anywhere. The proposed system was used to monitor only diabetes; future work can be extended to other related illness like heart alzheimer disease and dementia, cardiovascular disease, arthritis, asthma, cancer, crohn disease, and cystic fibrosis. Data privacy and security for IoMT-based monitoring of healthcare systems should be looked into for future work. Machine learning methods should be combined to solve the issue related to changing sensory inputs. Developing countries, especially African hospital, should be thinking of how to deploy IoMT in hospitals to reduce cost since it is feasible and economical. The collaboration of government, medical personnel, and researchers is very relevant to improve the implementation and deployment of IoMT in our hospital.

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Wearable Sensors for Pervasive and Personalized Health Care

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1 Introduction

There is a tremendous growth in the healthcare industry with various innovations in the field of medical technology [1, 2]. These innovations are aimed for the progress in the field of medicine that helps in treating patients with minimal resources and medical personals. The innovations in telecommunication have abundantly helped doctors in the field of health care to communicate with patients, take guidance from fellow doctors, share clinical information and furthermore to conduct certain clinical examination using mobile phones [2, 3]. Even though technology has developed and health care is incorporating innovations, there are clinical faults that can occur due to inaccessibility of enough data and records on time. One of the challenges for patients in rural zones is the difficulty in accessing medical help in emergencies. Healthcare industry also faces challenges in the administration of the industry, healthcare-related suppliers, and clinics which are directly related to the financial pressure. To overcome such challenges in the field of medical sector, pervasive health care stands forth as an innovation in the field of medical industry in serving people who are in need irrespective of their location and time. Pervasive health care is a system that is designed to provide medical care to the needy irrespective of the time at which they are in need or their location. Pervasive health care includes continuous health monitoring, emergency management, healthcare data access, and telemedicine [2, 4–6].

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_7

Table 1 Wearable devices monitoring parameters

Werable Device	Monitoring parameters					
Hexoskin biometric shirt	Heart rate	Respiratory rate	Number of steps	Distance traveled	Consumption of oxygen	Calorie burned
Jawbone UP3 fitness tracker	Heart rate	Running	Number of steps	Distance traveled	Food and liquid intake	Sleep stages
Striiv fusion bio fitness tracker	Heart rate	Sleep quality	Number of steps	Distance traveled	Calories burned	
Microsoft band 2	Heart rate	Sleep quality	Number of steps	Elevation, climbing, and running	Food, and liquid intake	Calories burned
Fit bit charge fitness tracker	Heart rate	Sleep quality	Number of steps	Elevation, climbing, and running	Food intake and liquid intake	Calories burned

Table 1 shows different products with the parameters considered for monitoring [7]. These different pervasive applications can be designed through innovative technologies.

Increased life expectancy is a need of every human, and it is been supported by improved technologies in the field of health care and medicine. It is necessary for the medical industry to develop low-cost and easy to use medical equipments that will help in health monitoring elderly and seek personal in remote areas. Pervasive and context-aware apps are identified as keys that could play a role in order to extend the quality life of patients suffering from various illnesses. A pervasive system in brief is nothing but a system that can collect health-related information from the patients with the help of wearable or no wearable devices that constitute sensors and map this data obtained from sensors to interpret the result [8].

When a patient has to visit a hospital for regular checkups, the health condition may deteriorate because of traveling [3]. There are also cases when there is a need of multiple visits for medical checkups and is time consuming. A good example is when a patient visits a hospital for checking blood pressure. Due to stress of traveling to the health center and waiting, there is a high possibility that the blood pressure may go high and give an inaccurate result [3]. Hence, for diseases such as arrhythmia, heart failure, and diabetes, it would be better if the patient is monitored at home rather than outdoors or in a hospital. Not only will the diagnosis be more accurate but also more effective. Therefore, these observations suggest that pervasive monitoring can lead to better results.

Body senor networks (BSN'S) or medical body area networks (MBAN) are wireless networked collection of wearable sensor devices. These provide ubiquitous computing where half the loop is feedback loop, and the other half is used for administration purpose. A person with diabetes can use BSN technology to allow network of wireless implantable and attached glucose sensors which not only monitor the level of insulin in the patient's body but are also used to provide a feedback using the data. Pervasive health care is not only used for monitoring chronic diseases at home, but it also can be used by the doctor when he wants to monitor a patient who is just out of surgery and is in hospital under observation. With the help of pervasive health care, the physician will be confident enough to send the patient home and also monitor him in his home environment [3].

Pervasive health care is defined from two angles. First is that pervasive computing or ubiquitous computing is proactive in nature and also provides ambient technology for health care and wellness of a patient. Secondly, health care is made available everywhere, anytime. Therefore, pervasive health care helps to combine vast technologies which will benefit others. Furthermore, pervasive computing is known as opposite to virtual reality because virtual reality is created by computers in pervasive computing. This will bridge the gap between physical and virtual world. These are also defined by three big terms, namely ubiquitous computing and communication and user-friendly interface. Ubiquitous computing means that computers are available everywhere, whereas pervasive computing means integrating sensors and ambient technologies to improve health and well-being. Ubiquitous communication means enabling communication anytime, anywhere with any things. User-friendly interfaces help the users by taking their suggestions into considerations. Pervasive computing technologies are in themselves a very well-defined technology and also have a multi-disciplinary research goals with unlimited research gaps in terms of hardware, communication, embedded hardwares and softwares, and sensor technologies [4].

To decrease the burden on the healthcare industry, using pervasive technology is a relevant solution. The usage of pervasive technology not only reduces the gap between the physical and virtual world, but also helps people in need to obtain the health services from the comfortable environment such as their homes with the use of wearable sensors.

This chapter gives an introduction to Internet of Things (IoT) and pervasive health care. Various health monitoring devices with their parameters are summarized to identifying advancement in the pervasive health care along with the features taken into consideration. A survey on various sensor devices for health monitoring is described in this chapter. The chapter is structured in such a way that it gives an introduction to IoT in Sect. 1 followed by architecture of wearable IoT in Sect. 2. Section 3 summarizes the various parameters identified for wearable sensor devices, and Sect. 4 gives a detailed description on wearable sensor devices. Finally, Sect. 5 concludes the chapter.

2 Wearables Architecture in IoT

Web availability is omnipresent and has brought forth a totally different worldview to healthcare industry. IoT is the idea of connecting of items which are physical in nature to one another or to the web to make easy data capture and communication for consistent pervasive sensing, information examination and data perception [9]. Throughout the years, from fundamental Internet providers to wearable web, the interest for interconnecting smart wearables has expanded. The patterns obtained from Google search shows that there is a chance of development and prevalence of wearable innovations in the field of IoT. Wearable IoT (WIoT) can be characterized as a mechanical framework that helps in connecting wearable sensors to empower tracking of human beings including well-being, health, practices, and other informations which in turn helps in improving people's personal satisfaction. Moreover, WIoT targets interfacing body-worn sensors to the clinical framework with the end goal that doctors can monitor the health conditions of patients who are at their home. Patients suffering from Parkinson's disease can use smart watches to sense variations in their body. WIoT is in their earliest stages, and there is a need to support its effective development and to empower the human services. A framework with high integration structure for WIoT is represented through Fig. 1. There are three major components in the framework classified as wearable body area sensors, Internet-connected gateways, cloud, and big data support.

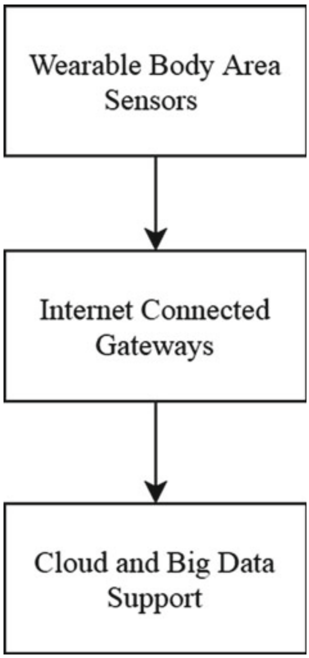


Fig. 1 Architecture elements of wearable internet of things

2.1 Wearable Body Area Sensors

Wearable body area sensors (WBAS) are components of WIoT which are devices that are generally wrapped around the humans body to capture health data and monitor the variations. WBAS is a fast emerging technology that is specifically used for monitoring health information using wearable devices. These wearable devices communicate with user and devices to easy and accurate monitoring. The major advantage of these devices is to collect real-time and accurate data. For example, wearable sensors, for instance, the BodyMedia armband [5] are applications that help in customers to keep up a working lifestyle.

The wearable sensors contain hardware like sensors that capture real-time data to collect precise clinical data of patients continuously. In case of wearable sensors, the contact between the sensor and the body helps in collecting the variations in health. Ring sensor for pulse oximetry, chest-worn ECG screen, and connectable biopatch all are a couple of instances of sensor areas that give continuos access to the body's indispensable signs. Wearable gadgets are woven into the garments textures so as to give heart rates to patients living in home, away from medical clinics and experts. There exist cloths where sensors embedded in materials are used to observe the changes in human body. The requirement for wearable sensors has prompted equipment scaling down and improvement of proficient approaches to lessen power utilization while working at clinically adequate gages.

2.2 Internet-Connected Gateway

Gateway helps in connecting the physical devices with the cloud servers. In some cases, gateway also performs the role of preprocessing the data in the edge computer before the data has been sent to the cloud. The data from the sensors is processed and compressed to transfer it to cloud server for storing health data. The gateways also transmit medical data like images and support video communication that helps in communication between the elderly at their home and the doctors for health analysis.

2.3 Cloud and Big Data Support

The applications developed combining wearable sensors and cell phones will capture and transfer the data to the cloud environment. The data stored in the cloud server will be accessible from anywhere by medical stakeholders for further analysis. Cloud-assisted BAS (CaBAS) is developing as an innovation that gives reconciliation of MCC and WBAS to encourage the development of versatile, information-driven pervasive social insurance. WIoT can get various noteworthy advantages from CaBAS [9], for example:

- Vitality effective steering conventions that can organize cell phones and wearable sensors for handshaking and consistent information.
- Occasion-based handling that can decrease undesirable information of wearable sensors.
- Information logs that can include action level data head of clinical information for upgrading the precision of AI calculations on the cloud.
- Secure information storage that incorporates encryption to store medical data in cloud server that maintains safety of data during access and transfer for medical analysis.
- Data access and transfer which would help in accessing medical data from anywhere for analysis and sharing of the same with various stakeholders for further examination.

3 Parameters Used for Wearable Systems

3.1 Heart Activity

Heart rate is an important feature that is considered while analyzing the signals of heart. Electrodes could be placed to monitor heart's movement. Silver chloride electrodes are used to analyze ECG for any clinical settings. Doppler effect is used in checking the heart muscles in case of remote consultation. To check if the heart is pumping properly, the change in blood volume is measured which is done by checking if there is any obstructions in the blood using photoplethysmography. The photoplethysmography procedure uses a light-emitting diode (LED) put at fringe locales, for example the tip of the finger or ear cartilage, to interpret light by means of a photodiode. Heart rate can likewise be checked by a phonocardiographic (PCG) sensor placed on chest. This was accomplished by setting an accelerometer to gage the vibration of the tangle brought about by the action of the heart and the developments related to breath [6].

3.2 Blood Pressure

Blood pressure (BP) is one of the parameters considered while monitoring health of a patient for symptomatic and asymptomatic health issues. High blood pressure can lead to heart- and kidney-related ailments. Various wearable frameworks for BP estimation have been created depending on regular estimation procedures like the oscillometric technique. To estimate the blood pressure, a wearable device called MediWatch [10] will be very convenient which uses blood vessels to capture the heartbeat waveform and computes the blood pressure [6].

3.3 Blood Oxygen Saturation

Optical transducers placed on the skin can decide the level of hemoglobin along with oxygen levels. Blood oxygen is an essential marker of a person's well-being knowing that an individual cannot stay if steady oxygen is not supplied to the cerebrum. The first device built for this was a finger ring which would measure blood oxygen saturation [6].

3.4 Respiration

Respiration is a significant physiological capacity that is multi-dimensional in nature. Respiration is related with the kinematics of the chest. The procedure called as inductive plethysmography is the highest level procedure to know the respiratory level of a person. This device has two wires, one goes around the ribs which the other goes around the abdomen [6].

3.5 Bio Chemical Measurements

Several techniques, for example, iontophoresis, electrophoresis, and sonophoresis, have improved the proficiency of the "extraction" of body liquids from the skin. Skin empowers noninvasive estimations of a few analytes including blood glucose, lactate, immunoglobulins, amino acids, and proteins. The technique for iontophoresis, that has been utilized for numerous decades, uses electrical flow to convey charged medicate mixes through the skin. In transdermal observation, features influence the exactness and unwavering quality of the measures are skin color change, surface smell, tissue thickness, breathing antiquities, blood stream, body developments, temperature, and pressure [10].

4 Wearable Health Devices

There are many equipments to monitor sleep, blood pressure, ECG, health, cardio vascular diseases, human activities such as walking, jogging etc. Some of the applications that are designed in monitoring health are briefly described below.

4.1 Patient Monitoring System

Personalized patient monitoring systems can monitor parameters such as heart beats, the rate of respiration, and temperature of the body or skin. This is basically done using a wearable sensor which can be used in human body parts. To personalize these devices for the patients, the data is collected and then adjusting the device according to individual patient's health conditions. This is purely done by health professionals so that the initial adjustment of device is done according to individual patients, and they get appropriate alerts as and when necessary. For instance if any patient with high-risk heart rates needs to be monitored continuously in a suitable environment, for such patient immediate alerts need to be generated when there is increase in threshold values. Such a system needs to forward an alert to the medical stakeholders for an emergency action to be taken. The main objective of such situation is to generate alerts for high-risk patients. This system should be designed in such a way that the patient or patient's caregivers are able to access, edit the health condition of the patient to view the symptoms. Additional activities like driving, exercise, and rest need to be entered into the application as this will amount to additional information which is very important for monitoring patient's health [5].

4.2 Smart Home Health Care

IoT gadgets are designed such that it can be used by seniors as well as individuals with exceptional consideration needs without much difficulty. IoT frameworks for home automation can give more security for senior citizens who live alone and can be made increasingly effective. This system empowers connected and customized human services and health administrations to the people staying alone and need medical assistance. Smart home will help in adjusting the room temperature if it finds that the body temperature of the individual has varied from the data collected from the wearable sensor. Semantic web advancements have combined with sensor information from various areas to produce significant knowledge and make predictions. This is achieved utilizing machine-to-machine measurement (M3) structure. The objectives of such system are to oversee and collaborate with heterogeneous gadgets deployed in homes, utilizing M3 system to produce significant level reflection from sensor information, joining sensor information from various areas to make novel social arrangements, controlling home computerization gadgets based on the individual's health and collaboration with M2M gadgets. The technologies such as 6LoWPAN, Bluetooth Low Energy (BLE), and NFC are appropriate for communication. NFC is valuable for a patient to check his/her well-being status, BLE can be utilized to accumulate data of a few patients, and 6LoWPAN can speak with any IPv6 empowered frameworks [11].

4.3 Context-Aware Real-Time Assistant

Pervasive computing has developed as a feasible arrangement equipped for giving assistive living to older people. The pervasive healthcare framework, context-aware real-time assistant (CARA) as seen in Fig. 2, is intended to give customized medicinal services administrations to older people by adjusting the human services for the old and helping the caretakers. Customized, flexible structure for CARA framework in a home condition gives setting sensor information combination just as irregularity location components that helps activity of daily living (ADL) investigation. The joining of rule-based and case-based thinking empowers CARA to turn out to be progressive and to adjust to a domain which changes by effortlessly retraining with some new case [12].

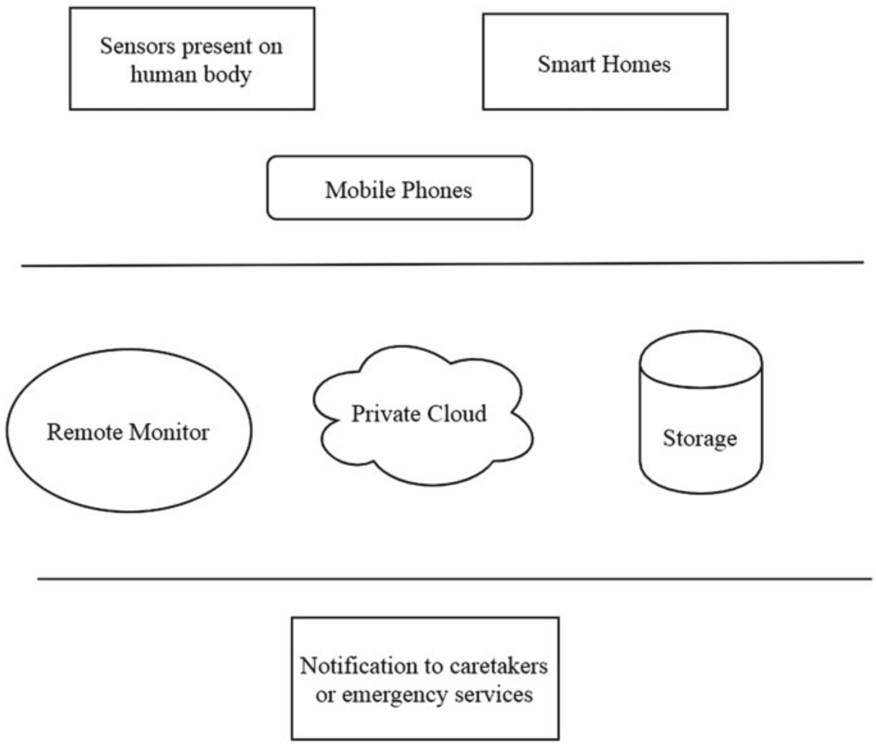


Fig. 2 CARA healthcare system overview

4.4 Personal Health Advisor System

Healthcare administrations, for example, health monitoring, and clinical conference should be personally based on context as seen in Fig. 3. The personalized healthcare administration gives health-related guidance to the client in the correct way and at the correct time. For productive preparation of context in healthcare personalization, the context is characterized into five classifications: personal health context, environment context, task context, spatiotemporal context, and terminal context. Personal health context comprises two categories: the physiological context and mental context. The physiological context has data like pulse, circulatory strain, weight, glucose level, and retinal examination. The mental context incorporates context like disposition, outrage, and stress.

Terminal focuses about the client's entry and gadgets. This incorporates data and properties like attributes of the terminal (screen size, shading nature of the screen vitality type, independence, OS, memory), interface (WWI, Bluetooth), terminal sort (PC, TV, PDA, SIB, hand telephone), and media (sound, video, text, and so on.). The key part is the personalization. It obtains various types of context from the knowledge base, produces healthcare guidance, and conveys the healthcare administration at the correct time. The personalization motor influences on the past context foundation for context securing. The personalization motor comprises three components: a healthcare counsel, a healthcare scheduler, and a healthcare connector [13].

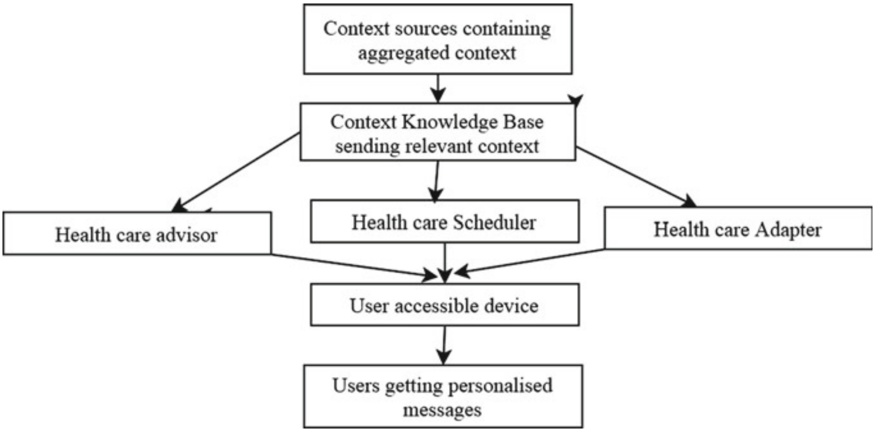


Fig. 3 Context-aware applications

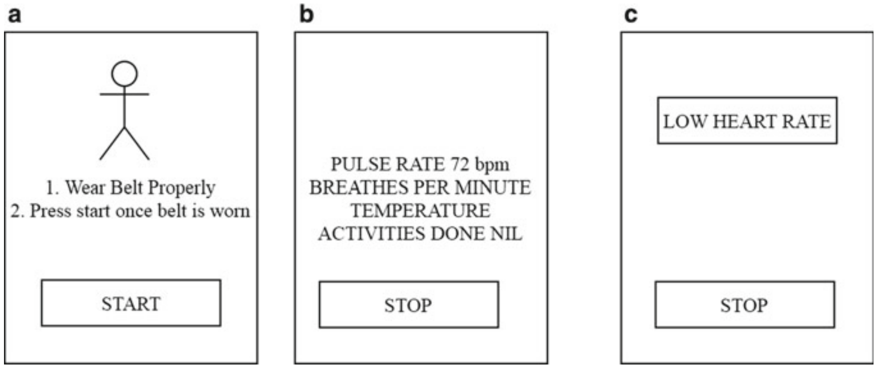


Fig. 4 Chest belt (**a**) real-time health monitoring in (**b**), and low heart rate alert in (**c**)

4.5 Personalized Sensor-Based System

Attributes such as heart rate, breathing rate, temperature, BP, and other activities are observed by wearables or convenient sensing gadgets that monitor a patient's activity. For this purpose, a mobile is used which is also called as mobile base unit that can communicate with the sensors via Bluetooth. This will be used for collecting information from sensors and also to send the details of analysis to the patients. The result obtained will be used for further analysis and to generate alerts. For example, if the analysis shows a low pulse as shown in Fig. 4, a message is sent asking the patient to take relevant practice measures for low pulse rate. The result from the analysis of data is sent to medical center (MC) administrators, who get the notices, assess the seriousness of the patient's health status based on the data obtained, and deal with the telemonitoring procedure between the patients and the health experts. This information could also be intimated to the health experts, who are empowered to see observing results through their framework such as the health professional platform (HPP) [14].

4.6 A Hybrid Mobile Cloud Approach for ECG Telemonitoring

Wearable body sensors are used to check the health condition of a person and also produce alerts if necessary based on the data collected and analyzed. The applications installed in cell phones will be able to gather information, for example, circulatory system data, temperature, pulse, and ECG from the wearable devices paired with the cell phone. Those clinical checking information can be given to the doctor for assessment or to a symptomatic program to naturally distinguish any variations from the normal physiological estimations and give the alarms to caretakers for immediate action. The utilization of convenient physiological and intellectual observing frameworks will empower doctors (and patients) to intently screen patient's health status and adequately give significant remedies without the emergency clinic visits. This kind of telemonitoring is especially viable for overseeing infections for old people, for example, diabetes, hypertension, and cardiovascular illnesses (CVDs).

The ordinary investigation is normally based on values obtained. Progressively, modern artificial intelligence (AI) procedures have likewise been widely examined and utilized in distinguishing the clinical issues via consequently looking at the irregular practices. The artificial neural network (ANN)-based ECG calculation can accomplish over ninety-five percent precision in distinguishing cardiovascular arrhythmia, and the SVM-based investigation can altogether lessen the measure of false cautions. This data is then transferred to the cloud [15].

4.7 Wearable Implants

The last decade has helped to advance the pervasive health paradigm which is also known as U-health and M-health which is ubiquitous health and mobile health. Looking into the evolution of these devices from a clinical perspective, there has been gaps filled between health and management of diseases. There are many wearable implants available for various diseases, and some of them are mentioned below in brief.

- **Chest sensor implants**: This is used for measuring glucose, temperature, and galvanic skin response. The clinical focus is for the diseases arrhythmia, diabetes, cardiac inflammation, obesity, and infection. The name of the devices used for this purpose is Cardio Mem [6, 16] and Dexcom [6, 16].
- **Eye sensor implants**: These are used for measuring glucose and intraocular pressure. The clinical focus for diseases is diabetes and glaucoma. The name of the devices used for this purpose is the Google contact lens [6].
- **Brain sensor implants**: This is used for measuring EEG, glucose, and impact forces. The clinical focus for the diseases is concussion, trauma, and epilepsy. The name of the devices used for this purpose is Check light, Pinnacle, and Neuro Pro [6].
- **Ear sensor implants**: This is used for measuring acceleration and audio response. The clinical focus for the diseases is clinical gait analysis and hearing loss [13].
- **Tooth sensor implants**: This is used for monitoring oral on goings and bacteria. The clinical focus for the diseases is infections in the tooth [13].
- **Wrist/arm sensor implants**: This is used for measuring activity levels, energy expenditure, EMG, EEG, and skin conductance. The clinical focus for the diseases is obesity, emotional stress, Parkinson's, stroke rehabilitation, and Neonatal care. Such a sensor is developed by company Nike [6].
- **Feet sensor implants**: This is used for measuring accelerometer and air pressure. The clinical focus is for the diseases obesity and clinical gait analysis [13].

- **Fingers/hand sensor implants**: This helps in measuring blood pressure. The clinical focus is for diseases arthritis, surgical training, and hypertension [6].
- **Hip sensor implants**: This helps in measuring hip replacement. The clinical focus for the diseases is a hip prosthesis [13].
- **Ingestible wireless sensor implants**: This is used for measuring temperature, heart rhythm, brain simulator, and auditory nerve. The clinical focus for the diseases is infection, deafness, blindness, knee, and heart replacement. The name of the devices used is the VitalSense, Evera, Second Sight, Cochlea, and Proteas [6].
- **Wearable for ambient environment implants**: This helps in measuring humidity and temperature. The clinical focus for the diseases is poisoning. The name of the device is Sensordrone [6].

4.8 Wearable Multifunction Physiological Monitoring Devices

Various wearable multi-boundary physiological monitoring frameworks have been formed and placed into viable use for health monitoring.

4.8.1 Wearable Patch ECG Monitor

Considering long-lasting ECG monitoring, present in monitoring system, requires an occasional substitution of the cathodes and low-quality ECG flags because of the development of terminals. The progression in wearable advancements has helped in the improvement of wearable patch ECG monitors which join to the skin, and no cathodes and wires are required. It empowers monitoring of patients while they are completing day-by-day exercises that will permit clinicians to all the more likely analyzing ECG illness.

4.8.2 Wearable Fitness Training Device

These days, people are more concerned about their health and exercise daily in order to remain fit. As of late, several organizations dispatch a number of new items which help in fitness and training like FuelBand, Fitbit Ultra, LINK Armband, and SmartBand [17].

4.8.3 Wearable Biofeedback Breathing Training Device

Biofeedback breathing training is a non-sedate, successful, low-cost, and non-obtrusive technique to monitor health conditions and help in regaining fitness.

Through managing breathing based on pulse fluctuation, respiratory sinus arrhythmia (RSA), or other input, the clients can figure out how to handle these noticeable signs and then to adjust physiological and mental states.

4.8.4 Mobile Phone-Based Healthcare Application

With the advancement of mobile Internet, health care has started to be developed in all the places so as to assist the patients and the hospitals to take care of treatment without much delay. For instance, application such as 5U doctor [17] app was developed in China which can provide appointments, give feedback, and give advices to patients.

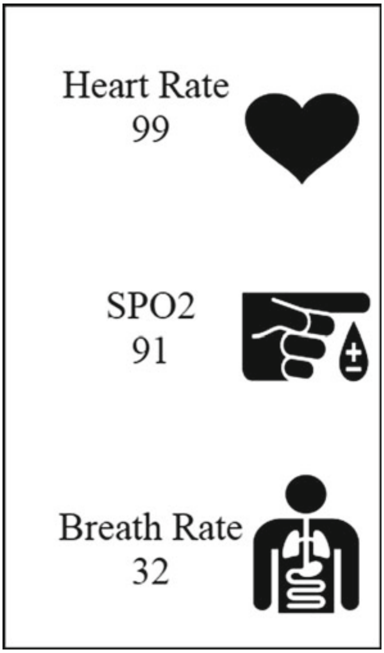
4.9 Sensors for Human Activity Monitoring

Sensors are placed in different places in human body to monitor activities of the humans, and it becomes easy to identify any change in health parameters under observation. The rapid growth is in the field of microelectronics, micromechanics, and many integrated optics which are similar to these technologies. These assist in developing sensors which can sense and measure the data more efficiently and accurately. Moreover, these equipments also have low-power consumption which is a great advantage. The temperature of the body is a common parameter which is measured to monitor the activity of a person. This will provide information with respect to the parameters that are under observation of human body. The next common parameter is heart rate. If there is a variation in the heart rate, then this will be an indication of any heart diseases. Also the level of emotions in a human can be measured by using human emotion recognition systems [18].

4.10 Activity Monitor

Wearable biosensor frameworks permit patients to be monitoring for a broad timeframe. With the development in innovation, such frameworks become increasingly minimized and can be utilized outside the medical clinic, consequently expanding the inclusion of the everyday exercises of patients. Additionally, the utilization of remote innovation turns out to be progressively normal, permitting remote monitoring of patients to be effectively accomplished. Remote innovation can be applied in two distinct structures: short-range and long-range correspondence. Short-range correspondence can send and get information from the wearable device to a close device by control unit. Also a normal cell phone can be used for this purpose. This leads to numerous prospects for the patients and users. It can also obtain health information extraction in the mobile phone as seen in Fig. 5. Information extraction and estimations are done in the mobile phone. In different frameworks, the

Fig. 5 Activity monitor



device controller performs health information extraction. In most wearable frameworks, basic programmed ON/OFF control is very normal. Nonetheless, this is very constrained and overlooks the real continuous need of the client as far as monitoring. For instance, if the ailment and pattern are truly steady, less regular estimations or shorter eruptions of estimations can be a stage for wearable biosensor and mobile phone monitoring [19].

4.11 A Human Context Recognition System

The growing nature of the population is a main worry of numerous nations since the number of elderlies around the world is increasing and many of them are staying alone. This circumstance presents new difficulties to existing healthcare frameworks, for example, the reduction in number of caretakers. It is trusted that innovations in medical field will be a helping hand for these problems. For example, by asking and training the elderly to carry on by using applications for healthy lives and hence decreasing the dependance of them on caretakers can lead to a happy living in their own homes. Several applications including ambient-assisted living for elderlies and assisting patients with constant ailments, for example, diabetes, psychological turmoil, or arrhythmia help people in monitoring their health-related issues without visiting a hospital for a regular checkup. Wearable sensors, like accelerometers or

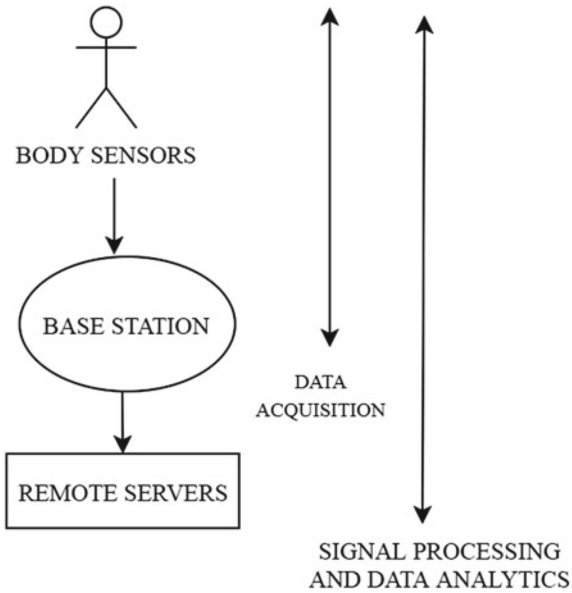


Fig. 6 Human context recognition system

ECG, are connected to get details about biomechanical, physiological, and environmental information. This information is examined to give assistance to caretakers who can take care of the treatment, change medicine, better investigation, or administer a patient's behavior. Human context recognition (HCR) offers constant monitoring, and the framework is shown in Fig. 6. In healthcare applications, sensors are utilized to obtain information during everyday life [20].

4.12 Smart Wrist Gadget

The wrist-worn gadget that is intended to monitor in a non-intrusive and subtle manner incorporates essential services like cardiovascular action recognition through photoplethysmography. The LEDs will indicate the battery's low charge and basic estimations such as estimations of pulse higher than 95 bpm when the client is sleeping. The alert indication is generated using PIC24F microcontroller that is used for obtaining signal, information stockpiling, and information correspondence [21].

4.13 Smart Wheelchair

The need to acquire the data on health status and movement of individuals who are handicapped has been prompting different brilliant wheelchairs models to develop smart wheelchairs. Various sorts of sensors for cardiorespiratory can be used to monitor through smart wheelchairs, some of the sensors are photoplethysmography (PPG), ballistocardiography (BCG), capacitively coupled electrocardiography (ccECG), contact electrocardiography (ETX-ECG), and skin conductivity based on e-material anodes. A brilliant wheelchair is developed which is based on the utilization of microwave doppler radar sensors which is non-electrical and non-mechanical, for cardiorespiratory monitoring [21].

4.14 Smart Walker

This device is used for getting details from sensors using doppler radar which help in giving physiotherapy for the patients. By utilizing the technology, the number of steps can be counted. Estimating the movements of the patients can be done through this, and the result can be sent to the doctors for further analysis [21].

4.15 Mobile Health

This includes using mobile phones for collecting and summarizing the data of the patient's health condition. This will lead to providing important information to the doctor, research personnel, and caretakers of patients. Moreover, this information is thus saved on the cloud. This will allow increase in any health data information and healthcare facilities expansion. The introduction of mobile health will lead doctors to diagnose diseases and track diseases. Mobile health technologies can be provided to the general public to create awareness of certain diseases. This also provides medical education and training for medical workers. The spread of these smartphone technologies will open many doors for supporting diagnosis, telemedicine, and remote diagnosis. Technologies such as web browsers, GPS, access to any web-based information for patients are also the latest technologies which improve the decentralized health systems [21].

4.16 Intelligent Emergency Management System

Mobile devices would recognize certain conditions by the actions of a user. A large number of clinical devices can be coordinated in the remote device. These would permit to give details about the pulse rate, circulatory strain, and level of liquor in a human body. Pervasive access to healthcare data would permit a patient to access the current and past clinical data. And for healthcare suppliers, approaching current and complete data so that this would bring about a diminished number of clinical mistakes. Likewise, a unique administration of clinical data could permit a patient to limit who can get to his/her clinical data and to what extent.

4.17 Human Daily Activity Recognition with Sparse Representation

Monitoring human activity through sparse signals means that the signal is a linear combination with very few elements in the base. Many signals in the real world are sparse. For instance, to view an image clearly, sparse representation can be used using Fourier structures. Although, the main aim is to implement in face recognition, human speech recognition, and object recognition. To obtain the activity of a human in daily life, the motion node sensor is placed on the hip of a person, and these sensors are placed to capture data when the person walks forward, walks left, walks right, goes upstairs, goes downstairs, jumps up, runs, stands, and sit's. This sensor is very small which is very advantageous as it is non-intrusive and can be attached to a person's body easily [22].

4.18 Patient-Friendly Wearable Design

For user's ease, the plan of new wearable devices such as wrist accelerometer is a relief because of the interfaces, and obtaining of data is also easier. Patients can cooperate with these frameworks easily. Preventive healthcare activities by both health frameworks and private health systems are developed so as to build the health quality for patients. The use of mobile phones permits the doctors to talk about medications, feedbacks on infections, and the capacity to adjust to new medicines. The amount of this data given to the patient can change to the person's advantage. An application may just give one line activities, for example, "walk energetically" or "run for 30 min today," an application can be made increasingly point by point as far as requesting that the patient do oxygen-consuming exercises of 20 min and an anaerobic exercise of 10 min [9].

4.19 Sleep Tracking Devices

Obtrusive sleep apnea (OSA) is a sleep issue since it has a direct effect on the personal health. Diminished psychomotor execution, conduct, and personality issue are a portion of the outcomes of OSA. Along these lines, continuous checking of this issue is a basic need in healthcare system. There are a few frameworks for OSA identification. The devices used are the A&D body precision scale for physical activity monitoring, heart rate PM 235 for physiological monitoring, MEMS sensor HTS221 for sleep environment monitoring, LM393 for snoring intensity monitoring, and Fitbit Flex Bangle for physical activity and status of sleep.

4.19.1 Measuring the Sleep Parameters

Sleep environment and sleep states are the factors which influence the quality of sleep. Sleep environment means the place which is away from noise and suitable for sleep. Sensors are used to check temperature and moistness of the room. The status of the sleep is got from the hours of sleep. For this purpose, movement sensors are used.

4.19.2 Measuring the Psychological Parameters

Elderly individuals experiencing OSA may experience the ill effects of different cardiovascular and respiratory issues during sleep. The pulse and wheezing power should be estimated. Heart rate has a solid connection with strokes and respiratory failures in individuals who have OSA because sleep issues impact the autonomic sensory system and can cause pulse variations. A pulse monitor set on the person's chest is utilized to monitor the pulse during sleep, taking into account that the time during the night is a high danger of coronary failure. The snoring force caused by wheezing is a significant issue of OSA, and its power is firmly associated with the seriousness of this condition that is the force of wheezing increments as OSA turns out to be progressively extreme. Consequently, it is important to distinguish wheezing and evaluate its power. This is done by a sensor module which is situated in the elder person's arm.

4.19.3 Physical Activity Parameters Measurement

A healthy and dynamic way of life is evading a stagnant way of life, performing physical exercises, and keeping up a healthy weight. Physical movements help in monitoring the physical exercises in user's everyday life which can be valuable to health. For instance, if a specialist has prescribed an older individual to do activities to reduce OSA, for example, strolling in his home or going for various strolls outside, it is good to know whether he consents to the plan. Therefore, a pedometer installed in a smart bangle is used to sense the amount of steps taken by the persons. Weight is identified as danger when it increases thus a minimum weight gain expands the chances of OSA advancement [20].

5 Conclusion

The integration of pervasive technology in medical field has been proved to be fruitful for the patients by making all the facilities available at any point of time irrespective of the location. This includes continuos monitoring of health, standard examinations, and observing patients from home and nursing care and treatment. This chapter discusses architecture of various wearable devices that help in healthcare systems and how integration of IoT has enabled them to be smart devices for pervasive health care which is a stepping stone to the development of healthcare industry. In this chapter, a survey on wearable sensor devices and the parameters associated for monitoring health-related activity in a pervasive environment is presented. The objective of pervasive health care is to monitor people living an independent life in their comfortable zone and ensuring continuous and no invasive health monitoring. Various wearable sensor devices and the parameters associated with the same are discussed in this chapter that are used for pervasive health monitoring. However, there is a need of in-depth research in the security of data captured from these devices. The data captured from wearable sensors and stored in cloud servers is prone to various attacks. Hence, these devices are to ensure security of information and privacy of individual's data. The future study will be to discuss on various attacks on the physical devices and the network during data transmission and the methods proposed in preventing these attacks.

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Adoption of Wearable Devices by Persons with Dementia: Lessons from a Non-pharmacological Intervention Enabled by a Social Robot

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1 Introduction

Wearable devices, specifically smartwatches and activity trackers, are the most pervasive Internet of Things (IoT) devices today. The wearable technology market, including activity trackers, is projected to grow, worldwide, from over $30 billion in 2016 to over $150 billion in 2026 [13]. Wearable devices can sense, gather, and store physiological data, which can be used to monitor and infer behavior toward support care for specific health issues. The proliferation of fitness trackers and smartwatches, the most popular wearable devices, has raised the interest in their use in health-care research [15]. This is particularly true for studies that require an assessment of parameters associated with physical activity and sleep [32].

The use of wearable technologies in the domain of health care has increased in recent years, with studies reporting the use of a wide range of wearable devices for different health domains such as health maintenance [9], disease prevention [33], and patient and disease management [27].

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_8

The adoption of wearable technology has increased in different populations [1], including older adults. However, this technology is not widely used by this population, and there is a need to raise awareness to the benefits associated with use of these devices [16]. Although wearable devices are perceived as useful by older adults [21], there are certain drawbacks with their use, such as discomfort, itching, sweating, and hampered monitoring to sensitivity, which could affect their acceptance [16]. In persons (older adults) with dementia (PwDs), these issues can be exacerbated and added to others resulting from the disease such as memory problems, a tendency to forget or lose things, resistance to change, or just refusal to wear them [8, 14, 20]. Hence, the adoption of wearable technology by PwDs is still a significant challenge and a primary requirement for initiatives which considering a 24/7 monitoring for long periods.

In this work, we report on the adoption process of wearable fitness trackers by ten PwDs who participated, during nine weeks, in a cognitive stimulation therapy (CST) enabled by a conversational social robot. The study aimed to get an in-depth understanding on the factors and strategies that influence the adoption of wearable technology. This is a preliminary stage to establish an Ambient Assisted Living (AAL) setting for dementia care where the analysis of data gathered by wearable devices can personalize the therapeutic sessions guided by the social robot and care plans for the needs and characteristics of each PwD. In the next section, we present a literature review about the use and adoption of wearable devices in older adults and PwDs. Section 3 describes the importance of wearable device adoption as part of the envision of an AAL setting where PwDs are monitored to tailor their care plans and a non-pharmacological intervention (NPI) guided by a robot social. In Sect. 4, we describe a study to monitor an NPI for dementia using wearable devices. Section 5 shows the results concerning the adoption process of wearable devices. In Section 6, we describe lessons learned and recommendations for future initiatives of the use in wearable devices in dementia populations. Section 7 discusses the results of the study. Finally, we present conclusions and future work in Sect. 8.

2 Use and Adoption of Wearable Devices in PwDs

The emergence of new research-grade wearable devices (ActivPAL, Actiwatch and GeneActiv) and new placement sites (wrist, ankle and waist) has led to even more diversification in the methods and metrics that characterize various aspects of human physical behaviors [2]. There are two ways that wearable devices are currently being used in lifestyle medicine. First, they are used to measure physical activity over a period of a week or more, thus providing objective data on an individual's habitual level of physical activity. In this way, they yield objective data on physical activity, eliminating the need to rely on patient self-report. Second, wearable devices are being employed in the area of behavior change, where they are used to motivate individuals to comply with a daily activity goal. From a patient standpoint, this increases accountability. From a healthcare provider's standpoint, this is useful because it provides information on compliance with behavioral recommendations [2]. Despite the increasing use of consumer wearables in medical research, these devices have not yet entered the mainstream of medical practice, and they have not been adequately validated in frail older adults or clinical populations [2].

There is also a need to determine whether wearable activity trackers are valid when worn by older adults and clinical populations, in particular PwDs. Most of the validation studies conducted thus far have involved young or middle-aged adults, and the results may not be generalized to older adults and individuals with disabilities [2]. However, this promising outlook is dampened by the large discrepancy between adoption rates and sustained use [28]. Findings from the USA show that, despite the estimated adoption rates higher than 35% by 2020, attrition rates are as high as 30% within the first six months of receiving it [18]. Variations in designs might better align with the preferences of various groups of users. What is adequate for users may not cover the needs of others. For instance, activity trackers for patients with chronic illness should focus on a customized regimen and specific levels of physical activities. In contrast, activity trackers for healthy office workers with sedentary behavior may include different features, such as reminding the user to engage in physical activities [29].

Concerning the adoption of wearable activity trackers among older adults, in [17], the results revealed that older adults in different tracker use stages liked and wished for different tracker features. Long-term users developed a habit of using the devices, while various strategies had to be used with the other participants to maintain interest in them. Social support through collaboration was the main motivation for long-term users, while the competition was for short-term users. Users who abandoned their devices indicated that their use was driven by curiosity to quantify daily physical activity rather than a desire to increase it. Long-term users indicate a greater number of pros in device use, whereas the others focused only on the cons. In general, a positive attitude was found in older adults toward the adoption of new technologies [25], having a clear understanding of its value for their lives [26]. Wearable activity trackers were uniquely considered more personal than other types of technologies; thereby, the equipment characteristics including comfort, aesthetics, and price had a significant impact on the acceptance in the elderly. Finally, the authors in [26] acknowledge that privacy was less of concern for older adults, but it may have stemmed from a lack of understanding of the privacy risks and implications.

Very few studies have been conducted about the use or adoption of wearable activity trackers in people with dementia. Three studies in which wearable activity trackers are used with this specific population are summarized below. The first [24] was focused on measuring sedentary behavior and physical activity of 37 older adults with and without dementia, living in residential aged care, using an actigraph sensor. In a second study [10], the authors assess the sleep patterns across the 24 h day in 15 community-dwelling people with dementia using an Actiwatch-2, while in a third study [30], the risk of dementia was evaluated in a controlled study with 87 older adults from the measurement of physical activity levels using a Fitbit Zip during waking hours. Regarding adoption studies, in a previous work [22] the design and preliminary results of a cognitive stimulation therapy for people with dementia in which participants were monitored using activity trackers were reported. Finally, in a study on wearable research in dementia [12], it was found that although it is an emerging area, there was good support from patients and the public for this type of research.

3 AAL Setting for Dementia Care

Tertiary prevention seeks to reduce the impact of established disease, in the case of dementia, by softening the negative impacts of the dementia-related symptoms and maximizing potential years of quality life [3, 23]. Thus, therapies and NPIs are commonly an essential component of tertiary prevention by care providers. However, PwDs experience the disease in different ways, based on their initial predisposing factors, lifelong events, and environmental conditions [4]. Hence, it is essential to support person-centered models to assess the individual needs and effectiveness of treatments in order to provide personalized NPIs as part of a tertiary prevention for the care of those who are living with dementia.

We envision an AAL setting to address individual needs and emotional reactions through a personalized intervention using a social robot, called Eva. The robot Eva has been used to conduct therapeutic sessions for PwD, who participate in recreational activities such as reminiscence, music therapy, cognitive games, and relaxation [6]. The approach is based on the use of wearable devices to monitor and assess participants' behavior to modify the content of the therapeutic sessions and the interaction strategies of the robot (see Fig. 1). Besides, primary caregivers can use the gathered information to define or modify a personalized care plan for each person.

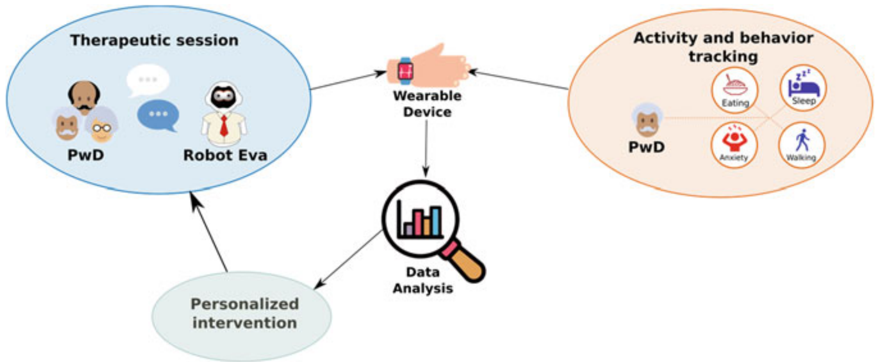

Fig. 1 An ambient assisted living setting for dementia care where wearable devices are used to gather information from PwDs in different situations (interacting in a therapeutic session with the social robot Eva, performing their ADLs) in order to generate personalized interventions and healthcare plans for the specific needs of a PwD

However, as we established in Sect. 2, it is not clear if a PwD accepts and adopts wearable devices for 24/7 monitoring throughout long periods. Thus, the adoption of wearable devices by PwDs is a prerequisite toward establishing an AAL environment with personalized interventions using the robot Eva.

4 Monitoring a Non-pharmacological Intervention for Dementia Using Wearable Devices

We conducted a study to assess the effects on the behavior of PwDs, who participated in a cognitive stimulation therapy (CST) conducted by the robot Eva. Results have shown that the CST had a positive impact on the frequency and severity of dementia-related symptoms (detailed results can be consulted in [7]). During the study, participants used wearable devices in order to get 24/7 monitoring, which provided useful information to validate changes in participants' behavior. Additional to these results, we analyzed the adoption of wearable devices by PwDs in this context. In this work, we focus on adoption findings during the CST as well as the challenges and opportunities to use wearable devices for PwDs.

4.1 Study Design

The study consisted of a CST that included 14 therapeutic sessions, two per week, where the robot Eva interacted with groups of three PwDs. A therapeutic session includes elements of music therapy, reminiscence, cognitive games, and relaxation, which combined lasted around 30 min. The study was conducted in the facilities of a nursing home where all participants live. Family members and caregivers who approved the participation of their relative were required to sign a consent letter. Ethics approval for this study was granted by the Bioethics Commitment of CICESE (CBE/PRES-O/001).

The type of wearable devices used in the study was commercial fitness trackers. We provided them for all participants to evaluate the adoption through prolonged periods. The use of the devices and issues emerging from it was monitored and documented in coordination with caregiver staff.

4.2 Materials and Methods

We used two models of fitness trackers by Fitbit: Charge 2 and Alta. The relevant data for the study were activity level, steps, and sleep monitor. Besides, we collected heart rate (HR) data from participants who used Charge 2 model. A preprocessing stage was conducted in order to standardize the collected data. We used the Fitbit WebAPI to gather data for each participant, including steps per minute, heartbeats per minute, and sleep minutes (day and night). Then, there were moved periods where the device did not record data, such as battery life, and participants did not wear it. We only included in our analysis those days where there were records for at least 50% of the minutes of the day.

The first method to analyze the adoption was the quantity of collected data. Thus, the number of days that participants wore devices is a first overview of their adherence to the wearable. In addition, we interviewed caregivers after the intervention to obtain their perspective on the adoption process. Three caregivers provided information for each participant. The interview script included questions about adherence, common uses, useful and new features, and significant issues of use and strategies to deal with them.

We analyzed the interview transcripts and framed the issues regarding the device's adoption by an extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) for PwDs [8]. Moreover, we conducted an analysis to establish recommendations for adoption and redesign of wearable devices based on the Dementia Design Considerations for Smart Health Technologies [11] framework, developed to guide the design of smart technologies for dementia.

4.3 Strategies to Promote the Use of Wearable Devices

In coordination with the staff of caregivers, we defined a set of strategies to avoid and deal with possible common issues of the use of wearable devices in PwDs. The strategies focus on aspects such as acceptance and everyday use, loss prevention, and battery charge and data synchronization. Moreover, we defined a quick data validation to detect unusual data during the synchronization process.

1. **Acceptance and everyday use**. Present the devices to the participants asa classic hand watch with additional features to track some of their activities, such as number of steps walked.
2. **Loss prevention**. The caregivers' supervisor defined a plan to monitor the use and localization of the devices. Each caregiver has to report on the location of the device at the end of their work shift.
3. **Battery charge and data synchronization**. We programmed visits by a member of the research team to the residence at least once a week to charge all activity tracker, synchronize the data from the internal memory to the cloud server, and review any contingencies caregivers might have regarding the devices.
4. **Quick data validation**. We analyzed data gathered at least once a week to detect unusual patterns of activity (e.g., null activity, an excessive number of steps, strange sleep activity). If unusual data are detected, we called caregivers (as soon as possible) to validate or discard this data from the dataset.

5 Results

Ten PwDs (6 females and 4 males), aged between 72 and 95 ($M = 82.4$, SD $= 8.4$) (see Table 1), participated in the study. Scores for Mini-Mental State Examination (MMSE) denote mild to moderate dementia ($M = 14.57$, SD $= 3.57$). Five of the participants wore a Fitbit Charge 2 h, while the other five used a Fitbit Alta. On average, they wore the devices for 54.4 days (see Fig. 2). After 22 days of use of the device, P3 left the residence and the study. After this, P10 was incorporated into the study to complete the therapy groups. We initially provided the wearable activity trackers to some of the participants to familiarize caregivers and participants with the device and the procedures implemented for their care, the handover with each change of shift, for charging the devices and synchronizing data. Due to technical difficulties, configuring two devices P8 and P9 received the device after the second therapy session.

Table 1 Information of PwDs who participated in the study

Id	Gender	Age	Days using the wearable device
P1	M	74	71
P2	F	76	39
P3	F	86	22
P4	F	95	70
P5	F	71	66
P6	M	90	63
P7	M	88	71
P8	F	86	62
P9	F	86	66
P10	M	72	14
AVG	6F/4M	82.4	54.4

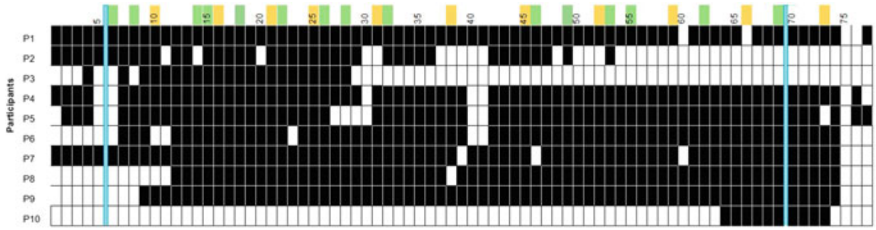

Fig. 2 An ambient assisted living setting for dementia care where wearable devices are used to gather information from PwDs in different situations (interacting in a therapeutic session with the social robot Eva, performing their ADLs) in order to generate personalized interventions and healthcare plans for the specific needs of a PwD

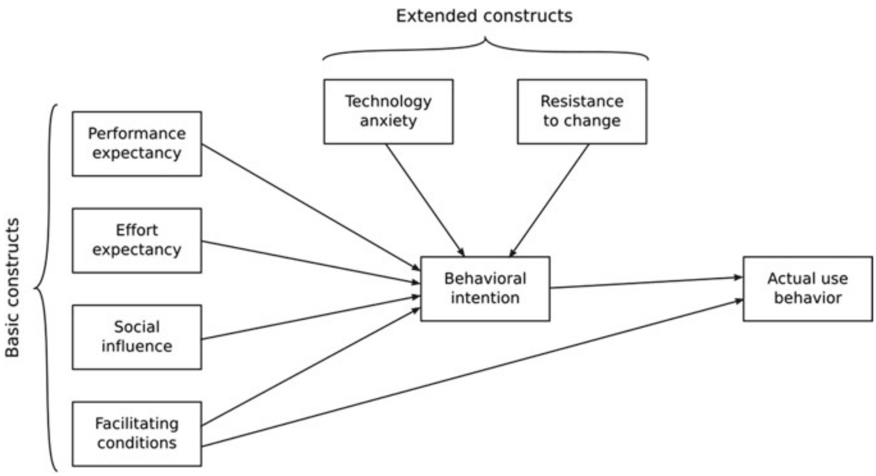

Fig. 3 UTAUT model as extended by [8]

Six caregivers also participated in the study (4 females and 2 males), including a supervisor who set some of the guidelines for the handling of the wearable device. They have an average of 3.2 years of experience as a caregiver in the nursing home. Three caregivers provided information for each of the participants. Thus, 27 interviews, which inform by nine participants (P3 was not included), were analyzed the adoption of wearable devices.

While one of the main advantages of using wearables in health studies is their capacity to record data 24/7, adoption and adherence are issues frequently faced in the use of these devices. Older adults, in particular, might find it uncomfortable to wear the device at night, or they might forget to put it on [19].

We framed the issues regarding the adoption of the device using the Unified Theory of Acceptance and Use of Technology (UTAUT) model [31] extended with two additional constructs: resistance to change and technology anxiety, deemed appropriate for technology adoption by older adults [8].

As shown in Fig. 3, the extended UTAUT model includes 6 constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, and resistance to change) that influence behavioral intention and actual use behavior. We present our adoption results with respect to each of the six primary constructs with regard to both the people with dementia and the caregivers.

5.1 *Performance Expectancy*

This construct relates to the perceived usefulness of the technology. In this regard, we told PwDs that by wearing the devices they would provide useful data to our study. Some of them reacted quite positively to this, and so did all the caregivers.

As a personal benefit, we told PwDs they could use the device to know the time of the day (none of the participants wore a watch when the study started), and that they could also track the number of steps they walk. Two participants expressed interest in this feature, with one of them asking the researcher several times how many steps she ought to walk each day. Also, caregivers used the devices as a subject of conversation with the residents and to convince them to use the device. As stated by two of them:

> C5: "At the beginning she liked it a lot [P2], and she used it. We asked her what time it was and she would answer."

> C3: "I even used the watch [as a strategy] when he [P1] became aggressive. I told him: "[P1] look you can see the time here, the steps and also this" and he [P1] got distracted. So I used the watch [wearable] to distract them and change their demeanor."

5.2 Effort Expectancy

This relates to the perceived ease of use of the technology. For the PwDs, we aimed at the device being as comfortable and innocuous as possible. The format of a wristwatch helps in this regard. Still, one participant refused to wear the device at night and would take it off and put it on her night stand. Also, two of the participants often refused to take off the device when it required charging and it took some convincing to make them give it up. In one instance, we had to wait until the battery ran off to convince P1 to give us the device to charge it. In another case, the caregiver gave P6 his own watch for several minutes while we charged the activity tracker. We left both of these participants the device for a few days after the study ended, until they agreed to give it up. In some of these instances, the device proved to be disruptive, as stated by one caregiver:

> C3: "…it was difficult to convince him [P1] to take it off, and we had to put it [the device] in a place where they could see it. For example, when he took a shower, he had to see it."

With respect to the caregivers, the use of the device put some additional work load on them. We supported them with a research assistant in charge of charging the device, and uploading the data, but still, they were responsible for making sure the device was used as much as possible and not be lost. In a couple of instances, a device went missing for several hours and once they realized this, it took a couple of caregivers several minutes to locate it.

5.3 Social Influence

This construct refers to how the social environment affects the behavior of the individual. At the start of the intervention, we told PwDs that other residents were also using the device, as an argument to convince them to wear it. One of the caregivers also reported that at least one of the PwDs encouraged others to use the device:

> C3: “[P4] used to tell [P2] and [P3] the functions of the watch in her own way:”It has this [function], and to see how we sleep” to try to convince them to use it [the device].”

With respect to the caregivers, they were instructed by the main caregiver to follow certain procedures regarding the use of the trackers. This is a form of social influence that had a positive effect on the caregivers to promote the adoption of the device.

5.4 Facilitating Conditions

This relates to the individual believing that there is an organizational and technical infrastructure to support the use of the system. Before the start of the study, we met with family members and caregivers to explain the objectives and procedures of the intervention, as well as their involvement. We also explained them the technical support we were going to be providing and means to contact the research team with any doubts or observations they might have.

Coordination between the caregivers, the main caregiver, and the research group proved effective. Visits to the facility by the researcher providing technical support were planned to be made three times a week, with additional visits made as requested.

5.5 Technology Anxiety

It relates to the fear of discomfort people experience when using technology, or thinking about using it. This construct negatively affects technology adoption and is commonly associated with aging.

Most participants did not experience anxiety with the activity trackers. Perhaps familiarity with similar devices (wristwatch) helped in this regard. However, P2 in particular expressed some reluctance to use the technology fearing that she could damage or lose the device. We tried different strategies such as telling her that the device was hers to keep and there was no problem if it got damaged. We also reminded her of the step counting feature, but she replied that she already knew how much she walked. Thus, we decided to withdraw the activity tracker but she continued to participate in the therapy sessions.

> C3: “From the beginning, she [P2] was very suspicious. She asked a lot [about the device] and we told her that it was to measure her steps, see how her heart beats, and how she sleeps, and she kept wearing it, but the following morning she didn’t have it.”

5.6 Resistance to Change

This refers to actions taken by individuals when they perceive a change as a threat to them. It also has a negative effect on adoption, and it is argued to be more prevalent among the elderly.

As expected, participants would often forget why they were wearing the device or even that they had it on them. P5, for instance, wore the activity tracker most of the time, but she would occasionally take it off and leave it somewhere in the residence. In a couple of instances, caregivers and researchers had to look for her device in the residence for a few hours before they found it. She was not very conscious of the device. For instance, a couple of times when we asked her for the device to charge it, she would tell us that she did not have it. Then, we asked her to show us her wrist and she was surprised to see that she was actually wearing it. She used a Fitbit Alta with the original band which is relatively easy to remove. These issues, memory loss, associated with the disease, required caregivers to constantly remind some participants to wear the device and the reason for doing so. One of the caregivers told the strategy she used in these cases:

> C3: "All of them when I took it [the device] off… what I did was to show them the functions it has, and with that, they kept using it."

In summary, coordination with caregivers, technical support, and the form factor of the device were relevant enablers for adoption. But, due to memory impairment participants had to be constantly reminded to wear the device and they could change their opinion from one day to the other. Activities that made wearing the device more salient, such as the need to take it off to charge it or bathing, proved challenging with some participants.

6 Recommendations for the Adoption and Redesign of Wearables for Dementia

Findings from the study show that, in general, the activity trackers were successfully adopted by the PwDs and caregivers, and these devices provide useful data to assess behaviors of interest for tertiary dementia prevention, since they are associated with challenging symptoms of dementia. In the form of discussion, we provide recommendations for the adoption of this technology and propose how activity trackers could be redesigned to be more useful for dementia research and care. We frame our recommendations using the Dementia Design Considerations for Smart Health Technologies [11] framework, developed to guide the design of smart technologies for dementia. Our proposals are organized along four domains (Fig. 4): cognitive decline; physical decline; social; and development.

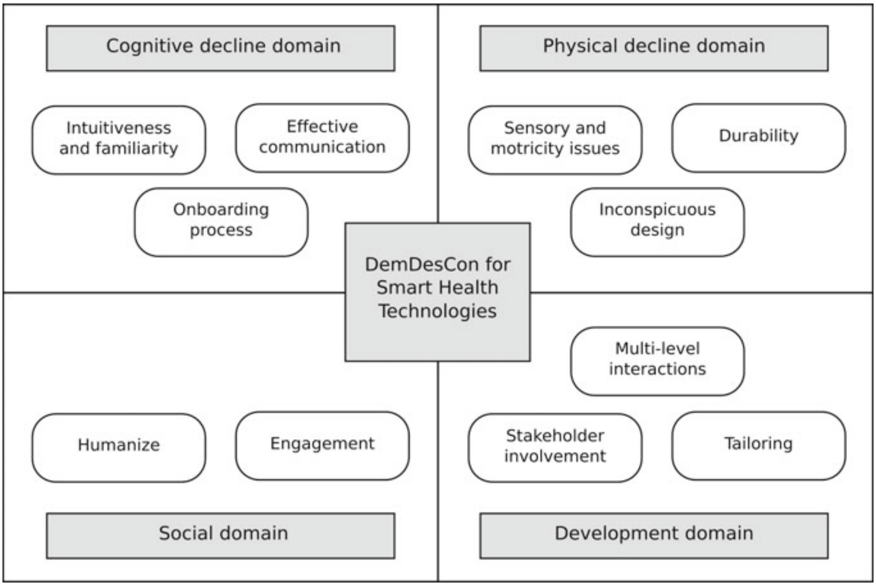

Fig. 4 Dementia design considerations for smart health technologies (DemDesCon for s-Health technologies [11])

6.1 Strategies to Promote the Use of Wearable Devices

6.1.1 Intuitiveness and Familiarity

Our recommendation is to simplify the functionality of the device. The form factor of the activity tracker as wristwatch proved effective. Most participants expressed interest in using the activity tracker, as a watch. However, some of its features proved distracting to some of them. For instance, P10 mentioned that the wearable would suddenly turn on at night when he moved, while P1 would often tap repeatedly on the activity tracker to look at the different information displayed, such as the time and number of steps walked. It is desirable to customize for each user the information that can be displayed, such as deactivating notifications.

6.1.2 Effective Communication

Make sure caregivers understand and can explain to PwDs the purpose of using the device. Caregivers know the participants well and know how best to explain to them why they should use them and potential benefits to them. The explanation they provide could be different for different participants and even vary for the same person overtime. If caregivers have a clear understanding of the device and its importance to the study, they will be able to explain it adequately to them.

6.1.3 Onboarding Process

We introduced the device gradually to understand initial issues with adoption. This proved particularly effective with caregivers, as it gave them the opportunity to become familiar with the additional work and adopt strategies for tracking the device and promoting its use.

6.2 Physical Decline Domain

6.2.1 Sensory and motricity issues

While the display of the device is relatively small, none of the users had difficulties using the smartwatch. However, the additional information displayed when tapping on the screen was not always sufficiently responsive. In particular, one participant tapped on the screen repeatedly and his device had to be charged more frequently. We recommend limiting the amount of information provided by the device and the gestures required to show it.

6.2.2 Durability

The device seems sturdy enough for everyday use by PwD. None of the devices we used was damaged in anyway. Furthermore, their cost is relatively low so that it could be replaced when needed.

The one issue with which we had additional care was water exposure. In this regard, we recommend using devices that are waterproof. During bathing, for instance, caregivers would usually take the activity tracker off, to which some participants offered resistance, or they might forget to put the device on again. The newer generation of activity trackers are waterproof and can be used in the shower. The use of waterproof devices can ease some of the burden on caregivers and reduce periods when participants do not wear the device.

An additional area of opportunity relates to charging the batteries of the device. While we charged the devices on our weekly visits and did not burden caregivers with this task, it would have been useful to have them periodically charge the devices for short periods, during activities such as bathing.

6.2.3 Inconspicuous Design

The wrist band format proved adequate for our study. However, for some participants other form factor might have facilitated adoption, for instance, by discreetly placing in a belt or shoe.

6.3 Social Domain

6.3.1 Humanize

This issue relates to promoting the device as a tool for socialization and independence. Some caregivers used the device as a topic of conversation with PwDs, for instance, by asking them the time of the day. The device could potentially be used to manage repetitive questions, if a person often asks when are they eating, the caregiver could encourage them to look at the watch to explain them how much time is left before lunch. This strategy provides them with anchors to reality and can help reduce anxiety.

6.3.2 Engagement

One of the participants expressed interest from the beginning on the step counting feature, asking a caregiver how many steps she was supposed to walk. These interests could be used to promote appropriate behaviors, for instance, inviting users to walk to increase the number of steps or helping them realize that it is time for bed or to take a bath. It would be desirable for the device to be customized with messages appropriate for each individual.

6.4 Development Domain

6.4.1 Stakeholder Involvement

Involving caregivers early in the process proved critical in achieving high adherence and understanding participants' behavior regarding the use of the activity trackers. This is an essential difference with respect to other studies with this type of device, which relies only on the participant. On the negative side, tracking the location of the device and promoting its usage impose additional burden on caregivers. Our recommendation is to add an additional personal or redistribute work load to account for these additional responsibilities. It would also be desirable to modify handover formats to track the location and usage of the device at the end of each shift.

Estimating participant dropout is recommended for studies involving older adults and particularly those with dementia [5]. When using activity trackers, these attrition rates should be increased to account for those not willing to use the device at some point in the study.

6.4.2 Tailoring

We used the wristbands that ship with the activity tracker in our study. However, some proved to be too big for their wrist. It would be convenient to have different sizes and materials and even encourage them to select one to their liking, even allowing them to change it during the study. Having bands of a different color and material would also be useful to distinguish the device of each participant. In one instance, a caregiver mistakenly switched the devices of two of the participants, until he realized this a couple of hours later.

6.4.3 Multilevel Interactions

Being able to personalize the functionality and information provided by the device would be useful. For some PwDs, it might be desirable to minimize functionality, perhaps just displaying the time of day. In contrast, other users might be interested in tracking the number of steps they walk or might benefit from receiving messages indicating it is time for them to go to bed. This tailoring could be similar to that provided in some activity trackers that are being commercialized for children, such as the Fitbit ACE, which requires parental consent and allows parents to customize the services the user can access.

Finally, some of these commercial activity trackers only provide summative data, reporting the number of minutes of different levels of activity per day. Having access to raw accelerometer and gyroscope data could allow using alternative activity and behavior recognition classifiers tailored to frail older adults to improve precision. In addition, researchers could be able to calculate heart rate variability that is associated with changes in mood and the manifestations of anger. There is also early work on detecting anxiety using heart rate variability and accelerometer data that could be particularly useful for the assessment of symptoms of dementia. In addition, including an audio sensor could allow to perform speaker diarization and thus assess behaviors associated with socialization.

Table 2 shows a list of dementia-related symptoms that are associated with behaviors that can be measured with activity trackers. This includes measures we obtained in our study, such as daytime sleep and activity changes, as well as others (indicates in italics), measures that can be obtained from new sensors (also in italics), or that could be derived from existing sensors if raw data were available.

7 Discussion

We conducted a study on the adoption of wearable devices by PwDs toward an AAL setting for dementia care. In this setting, individuals are monitored by wearable devices to personalize their care plan, including tailoring an intervention enabled by a social conversational robot. The results provide evidence of the feasibility of the

Table 2 Dementia-related symptoms that can be assessed from measures obtained from sensors in activity trackers

Dementia-related symptom (NPI-NH)	Behavior	Measure	Sensor
• Isolation • Depression	• Daytime sleep	• Minutes of sleep during the day • Sleep periods during the day	• ACC[a] • PPG[b]
Apathy	• Activity level • *Socialization*	• Number of steps • *Minutes of light/moderate/intense activity* • *Number of social interactions* • *Balance of social interactions*	• ACC • *Microphone*
Aberrant movement	• *Aimless wandering* • *Restless movement*	• Number of steps • *Frequency of abrupt changes in movement* • *Respiratory rate*	• ACC • PPG
Agitation/aggression	• Mood changes • *Screaming/verbal aggression*	• HRR[c] • *HRV*[d] • *Blood pressure* • *Number of screams*	• PPG • *Blood pressure* • *Microphone*
Anxiety	• *Restless movement*	• Number of steps • *Minutes of light/moderate/intense activity* • *HRV*	• ACC • PPG
Nighttime behavior	• Night wandering • *Restless movement*	• Sleep duration • Sleep interruptions • Steps between sleep periods • Nighttime sleep	• ACC • PPG

In italics are sensors and measures not currently available in the devices used in the study but that could be incorporated or derived from current sensors
[a]Accelerometer sensor
[b]Photoplethysmography sensor
[c]Heart rate reactivity
[d]Heart rate variability

sustained use of activity trackers during prolonged periods by PwDs. However, there are issues and lessons learned which we (and other research teams) should consider for successful adoption of this kind of wearables on the dementia population.

According to our literature review, there are only a few studies that report the use and adoption of wearable devices by PwDs. However, previous studies reported adoption findings that agree with ours. In [17], authors established that social support through collaboration was the primary motivation for long-term use of wearable devices in older adults, while our results show that the caregivers played a crucial role in motivating and promoting the use of devices. Due to dementia-related symptoms such as memory impairment, and disorientation in space and time, it is necessary to enact strategies to motive the adoption through social interactions. Nevertheless, it should be considered that personality, beliefs, and the way in which each individual experiences the symptoms of dementia can create tension in the use of the device; therefore, other types of strategies should be explored.

The results show a proper adoption of wearable devices for long periods. Some of the participants even showed excessive attachment to the devices. However, due to symptoms such as delusions exhibited by the false belief that their things could be stolen, this became a problem for caregivers who had to deal with this situation when they had to remove them for personal hygiene activities or battery recharging. Therefore, future initiatives have to consider each individual's symptoms to prevent these kinds of problems and enact appropriate strategies to deal with it.

The analysis of the data gathered from wearable devices can complement results for specialized instruments to assess behavior and quality of life in dementia. However, not all domains and symptoms can use such data for an in-depth analysis. Restrictions about the type of data and sensors of the device should define what can be measured. In Table 2, we proposed features (sensors and type of data) of wearable devices for a set of dementia-related symptoms, but future studies need to consider what they will measure and which device they will use to collect useful data.

8 Conclusions

We conducted a study to assess the behavior of ten PwDs who participated in a CST guided by a social robot. Participants were monitored 24/7 using a wearable fitness tracker to assess behavior changes reported by their caregivers via specialized instruments. Besides this objective, we conducted a parallel analysis for the adoption of wearables during the CST. Thus, this work focused on how PwDs use wearable devices and how their caregivers perceive the adoption process.

Our results on adoption provide evidence of the feasibility of using wearable devices in studies with PwDs, when the device needs to be used 24/7 for a prolonged period. Lessons learned and recommendations can be useful for researchers with similar studies, including high participation of caregivers to motivate the use of devices, considering that some PwDs can refuse their use or stop their use without any particular reason. We also proposed redesign considerations such as the addition of sensors and raw data collection to monitor and infer behaviors associated with dementia-related symptoms to provide personalized NPIs and care plans. As future work, we will focus on the proposed AAL setting for dementia care through the personalization of the social robot's intervention based on data collected by the wearable devices.

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Smart Wearable Technology for Health Tracking: What Are the Factors that Affect Their Use?

Sevgi Ozkan-Yildirim and Tansu Pancar

1 Introduction

Wearable devices are rapidly gaining importance in parallel with their increasing capabilities. Wearable devices are able to collect very diverse vital information about users such as daily step count, sleep duration, heart rate and blood pressure with the help of various sensors, they conveniently provide this data to users, and users are making use of this data in numerous ways [1]. In such an area where variety is constantly increasing, it is important to understand which factors influence consumers' intention to use wearable mobile devices. Technology acceptance models such as TAM and UTAUT and their variants are powerful tools for understanding these factors. Among various acceptance models, although TAM is the most popular one, UTAUT2 is more suitable for wearable devices as it has a focus on consumers. This study explores the factors affecting consumers' decision of using these devices based on UTAUT2 model, newly proposed additional constructs and open-ended questions.

A survey with 366 participants was conducted, and the results were quantitatively analyzed. In addition to the survey with multiple-choice questions dedicated to constructs in UTAUT2 model, another survey with open-ended questions was also completed. This second survey included six questions allowing the participants to further explain their usage of wearable devices. Responses to these questions revealed valuable insights regarding the expectations of users from wearable devices.

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_9

This chapter aims to understand important factors affecting consumers' acceptance of wearable devices to track health information. UTAUT2 model is extended with new constructs and both models are tested, and results are presented and compared. The main contribution of this chapter is showing that factors affecting acceptance of wearable devices usage vary significantly depending on age, gender, and experience with the technology.

It is seen that habit and performance expectancy are by far the most dominant factors influencing behavioral intention to use, and hence, further breakdown of these factors is likely to provide better insights. Effect of performance expectancy (PE) on behavioral intention (BI) was found to be more important for males. Furthermore, it is observed that both UTAUT2 and the proposed model perform much better for male users. Another relevant finding is that the answers to open-ended questions emphasize the importance of price although quantitative analysis did not highlight price as an important factor. This indicates the importance of hybrid approaches in technology acceptance studies which supports the findings from quantitative analysis with qualitative data from interviews or open-ended questions. It is seen that side-benefit expectancy (in our case wearable device's being fashionable and stylish) is the most important fourth factor after performance expectancy, effort expectancy, and habit. Not surprisingly, SBE is found to be relatively more important for younger users compared to other user groups. Neither the quantitative analysis nor the open-ended questions show that privacy is an important factor for the wearable device users. This might be due to the limitation of our study and reaching users with some particular devices (fertility trackers, and neurological monitors) may reveal the importance of privacy in acceptance of wearable devices in health domain.

This chapter is organized as follows; next section briefly presents fundamental models on user acceptance. In Sect. 3, proposed modifications to the UTATU2 model and the research gap are presented. Section 4 contains the detailed analysis of the survey and open-ended questions. Section 5 is dedicated to the interpretation of the findings from Sect. 4. Section 6 summarizes the whole study and the findings with remarks and limitations.

2 Literature and Background Information

Mobile health or mHealth is defined as the use of portable electronic devices including smartphones or wearable devices to provide health services and manage information such as health history or vital information [2]. Mobile health applications enabled by wearable devices are increasing in the consumer devices market. The diversification in sensor types and increasing accuracy helped these devices to provide better measurements and more detailed health data. Due to the ubiquitous nature of mobile devices, mobile health is also available anywhere, at any time [3].

Wearable medical devices market size was valued at over USD 9 billion in 2018 and is expected to witness 39.4% [4] compound annual growth rate (CAGR) from 2019 to 2025 The global mHealth market size is expected to reach USD 316.8 billion by 2027 [5]. Although wrist-worn devices like smartwatches and smart bands constitute the majority of wearable devices as high as 95% [6], the variety of device types and usage purposes increases. Understanding users' main purpose to use these devices is an important step to evaluate the adoption mechanism.

It is possible to separate previous research on wearable devices in two main categories, technology-related studies and user-related studies. The first group contains studies related to technology including power consumption, sensors, mobile technologies, communication, and connectivity-related research. The second group includes studies related to users, which can be listed as clinical studies, development of systems for health professionals or medical education and technology acceptance studies.

Acceptance and adoption of new technologies by organizations and individuals is a well-studied and established area. There are many research studies applying previous models or proposing extensions to existing models with additional constructs or modifications. Technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) can be listed among the most popular models. These models are applied in different domains or with different target audiences. Extended unified theory of acceptance and use of technology (UTAUT2) model focuses more on individuals rather than organizations and promises to be more useful at understanding consumer's adoption of technology. These models will be explained briefly in the following pages.

In parallel with the advances in technology, the role of technology in our lives is increasing continuously. This leads to researches having the aim of understanding the motives behind individuals' and organizations acceptance of technology and adoption of new applications, tools and information systems. Technology acceptance model (TAM) [7] was proposed in the late 80 s and dominated the area nearly two decades especially from the organizational perspective. TAM continued to be the leading model in technology acceptance domain and applied in various contexts which also revealed the limitations of the model.

In 2000, Davis and Venkatesh improved the model with new core constructs, which was named as TAM2 model. In 2003, Venkatesh proposed a new model, combining previous eight models in order to obtain a stronger model, unified theory of acceptance and use of technology (UTAUT) [8]. The new model provided better results on the acceptance of technology, but it also focused on organizational perspective. As technology solutions are rapidly increasing their share in every aspect of daily life, the boundaries between technology and non-technology domains are fading away. This trend is causing the acceptance of new technologies by consumers to be impacted by non-technology factors like fashion, environment concerns, and social acceptance.

With the increase of information systems usage by consumers, the UTAUT model turned out to be insufficient and an extension to UTAUT model, UTAUT2 was developed by Venkatesh in 2012 which strengthened existing model with three new constructs specifically added for individuals [9]. Three new constructs, "Hedonic Motivation", "Price", and "Habit" were added, and "Voluntariness" is removed.

In below sections, TAM, TAM2, UTAUT, UTAUT2, and an extended version of UTAUT2 model will be explained briefly.

2.1 TAM Model

Davis suggested two main constructs in the first version of technology acceptance model (TAM), perceived usefulness and perceived ease of use. Psychological theories aiming to understand behavior, theory of reasoned action [10], and theory of planned behavior [11] contributed to TAM. These two theories used "Behavioral Intention" which is defined as a person's perceived likelihood to engage in a given behavior [12].

"The degree to which a person believes that using a particular system would enhance his or her job performance" is defined as "Perceived Usefulness (PU)" by Davis and "the degree to which a person believes that using a particular system would be free of effort" is defined as "Perceived Ease of Use (PEOU)". Davis suggested a link between perceived ease of use and perceived usefulness. The relationship between these two constructs and their effect to actual system usage is shown in Fig. 1.

Perceived usefulness (PU) is both used as a dependent variable (due to being predicted by PEOU) and as an independent variable directly predicting behavioral intention (BI).

TAM is widely used in various contexts since 1989, and several studies were published as validations and extensions of TAM model. In 2003, Lee analyzed the evolution of TAM and divided it into four periods, introduction, validation, extension, and elaboration [13]. Many studies used TAM as a base model and proposed extensions and new constructs for various domains, user groups, and contexts. In a meta-analysis study, 88 TAM studies were evaluated and stated TAM measures to be robust and reliable [14].

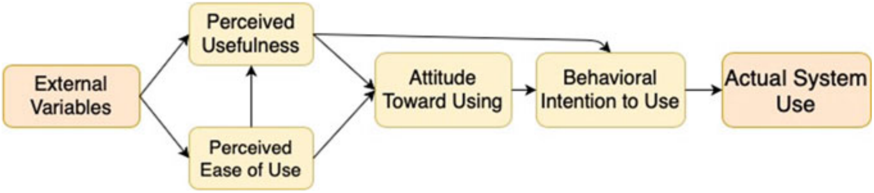

Fig. 1 Technology acceptance model

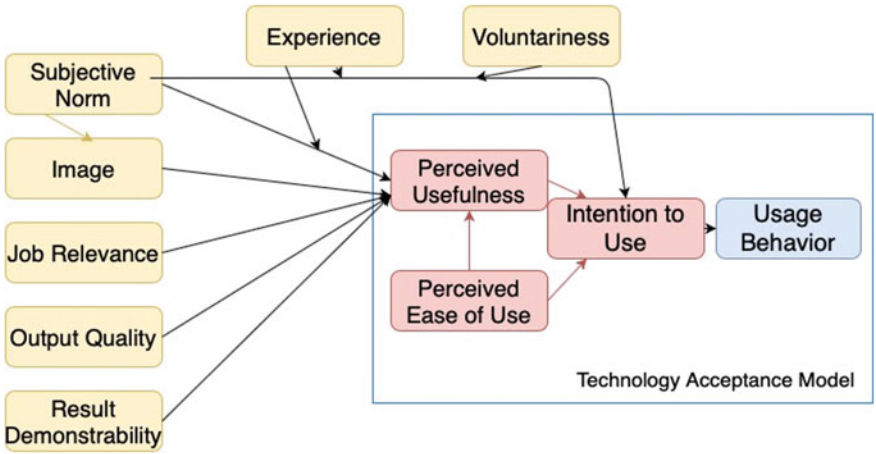

Fig. 2 TAM2

2.2 *TAM2 Model*

In 2000, Venkatesh and Davis modified TAM model and included new core constructs which can be listed under two groups, social influence processes (subjective norm, voluntariness, and image) and cognitive processes (job relevance, output quality, and result demonstrability) besides "Perceived Usefulness" and "Perceived Ease of Use" [15]. By adding, social influence processes, TAM2 enabled to keep record of individual's connections (i.e., managers or peer workers) with the construct subjective norm (SN). The TAM2 model is shown in Fig. 2. This model includes the concepts of voluntariness and experience which was not explicitly mentioned in original TAM model, in order to have a better understanding of technology adoption in organizations. TAM2 model proved to work well in both voluntary and mandatory scenarios, where subjective norm is effective in mandatory cases but not effective in voluntary cases.

2.3 *UTAUT Model*

In 2003, Venkatesh summarized prior theories in order to obtain a better performing result and listed core constructs of these theories and examined their importance on behavioral intention and use behavior. The UTAUT model is proposed with four main constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Figure 3 shows the UTAUT model with root constructs obtained from the previous theories.

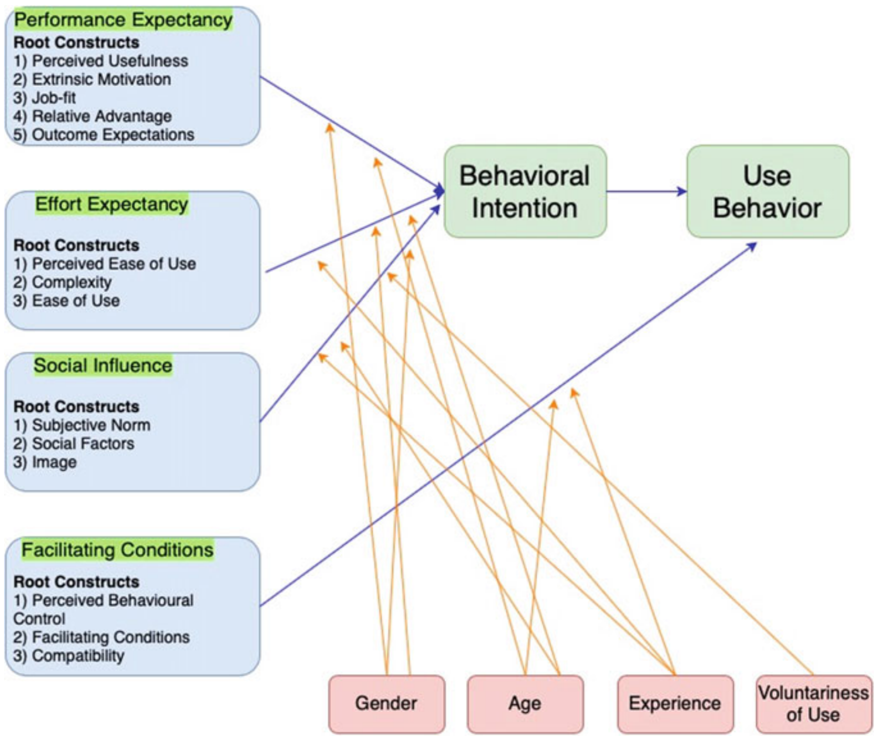

Fig. 3 UTAUT model

Besides main constructs, there are also four moderating variables such as gender, age, experience, and voluntariness of use. Similar to TAM and TAM2, UTAUT model also focuses on the use of technology in organizations.

2.4 UTAUT2 Model

The unified theory of acceptance and use of technology (UTAUT2) model was developed in order to customize the previous UTAUT model for individuals, especially consumers [9].

Four core constructs defined by UTAUT model were directly adopted [16, 8] and listed below. Performance expectancy is defined as the "degree to which using a technology will provide benefits to consumers in performing certain activities" [8]. Effort expectancy is defined as "degree of ease associated with consumers' use of technology" [8]. The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology is named as social influence [8]. The fourth and the last core construct is facilitating conditions which is defined as consumers' perceptions of the resources and support available to perform a behavior [8].

One of the moderators in UTAUT model, "voluntariness", is removed because it is valid for organizations, where new technology is mainly proposed by the management, but for the case of consumers, intention to use the new technology is mostly voluntary.

The UTAUT2 model proposed three new constructs (hedonic motivation, price, and habit) in addition to the four existing constructs in UTAUT model. Hedonic motivation, which can be defined as the enjoyment of using new technology, is conceptualized as perceived enjoyment [17].

In the organizational context, employees do not care about the cost of new technology, and previous models did not include any construct related to cost and price of using new technology. However, from consumers' perspective, price is an important parameter since users are responsible for the costs [18, 16].

Habit, the third construct added to the former model, is defined as the extent to which people tend to perform behaviors automatically because of learning [19] The Venkatesh's UTAUT2 model is shown in Fig. 4.

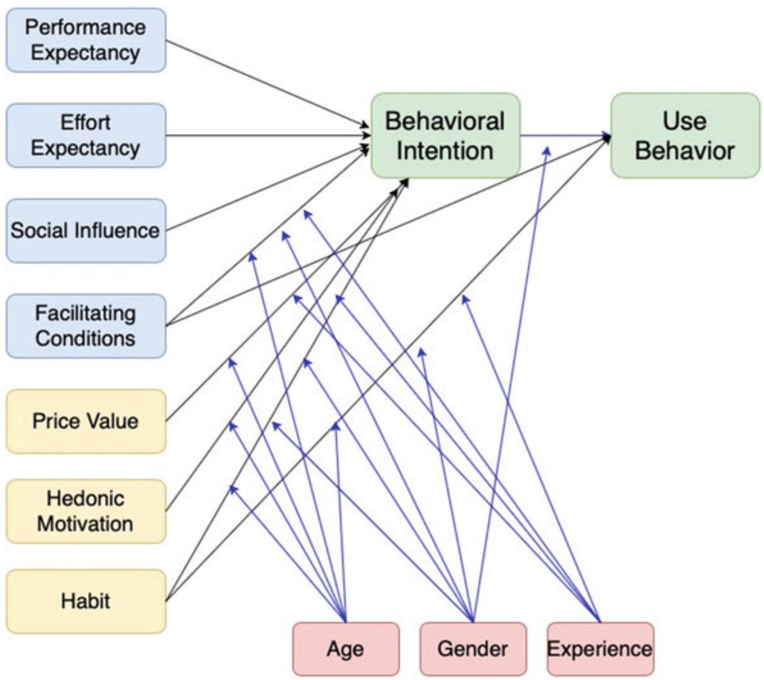

Fig. 4 UTAUT2 model

3 Proposed Model

3.1 Research Gap

Mobile health applications are proved to be very useful in preventive healthcare [20] and publications on wearable devices technology for mobile health research show an increasing trend in the last 10 years period. Technology-related topics dominate the area, and most of the publications focus on technology such as sensors, battery, communication technology or data analytics. Although the same trend is valid for publications on user-related topics including technology acceptance studies, they are few in numbers and constitute less than 10% of all publications between 2010 and 2019 [21].

In previous sections, technology acceptance models were examined including TAM, UTAUT, and UTAUT2 models. It is seen that TAM model, which is criticized for not being suitable for individuals, contrary to its success on analyzing technology adoption by organizations [22], is still the most dominant theory on technology adoption in mobile health and wearables area. The extended unified theory of acceptance and use of technology (UTAUT2) [9] which focuses on how consumers adopt new technologies on an individual basis seems to be under-appreciated in mobile health and wearables studies. Furthermore, there are several factors such as privacy, current health status, health expectancy which are not covered by UTAUT2 but worth analyzing to see how they influence the adoption of technology in the mobile health area.

3.2 Proposed Model and Modifications

In our research, we applied UTAUT2 model in its original form and also with proposed modifications which will be explained in the following paragraphs. Five new constructs (side-benefit expectancy, privacy, perceived health status, future health expectancy, and mere exposure) were added to the original model. Side-benefit expectancy is proposed as a new construct to extend UTAUT2 model in order to understand the users' expectancy from new technology besides its main purpose. For example, a smart wrist band, which is used to track the number of steps and heartbeat, can also be used as a stylish accessory. Being stylish does not affect the performance of the wrist band but can affect the user's decision to use or not. Fashion is likely to be an important aspect of wearable device adoption [23]. There are many studies examining the link between visual attributes to users' emotional attachment to these products, and how this link effects user acceptance [24, 25]. Furthermore, environmental friendliness (e.g., green-products) or symbolizing high social status can also be examined as side-benefits expected from the technology.

Privacy is an important concept regarding consumers' acceptance of new technologies [26] especially on an individual level. Privacy is defined as the willingness of consumers to share information over the Internet [27], and the privacy concept can also be defined as an individual's right to isolate their information from other people [28]. The importance of privacy is also related to the sensitivity of health information collected by wearable devices and mobile applications [29]. Individual's identifiable information should not be available to third parties including other individuals, companies or organizations, and in case this data is used by others, the owner of this data should have control over the use of this data. Previous models mainly worked on the organizational perspective, and the privacy of users was mainly related with trust in the organization. However, from consumer perspective, information on acceptance of new products and services can be used for various purposes (ranging from targeted advertisements to pricing of insurance). The addition of privacy construct to UTAUT2 model is expected to improve the overall performance of the existing model. Two new domain-specific constructs focusing on healthcare are proposed:

- Perceived health status
- Future health expectancy.

Measuring users' perception of his or her own health status is critical in understanding the intention to use these devices. Newly introduced construct, perceived health status, aims to understand how healthy the user feels himself or herself. Perceived health status is defined as the degree to which a person rates his or her own health status. Being healthy means not only the absence of disease or injury, but also includes overall physical, mental and social well-being [30].

Besides, perceived health status, it is also important to learn the user's expectancy for his or her future health status. The expectancy of future health may provide valuable information regarding the intention to use wearable mobile devices to track and improve the user's health status. Future health expectancy is defined as the degree to which a person believes that his or her health status will be in the future compared to his or her current health status [31].

Repeated exposure of an individual to a stimulus object enhances his attitude toward it [32]. The authors believe mere exposure is one of the important factors on acceptance of technology from consumer perspective, and hence, we propose it as a new construct to the UTAUT2 model. Better-than-average (BTA) effect is the phenomenon that people rate themselves more favorably than an average peer on most trait dimensions [33–35]. Due to BTA effect, under mere exposure to new technology through other people, individuals are likely to have the over-confidence regarding effort expectancy and facilitating conditions. The proposed model is shown in Fig. 5.

4 Survey and Analysis

The data was collected through an online survey which was active between December 2017 and May 2018. The completion rate of the survey was around 30 percent. After

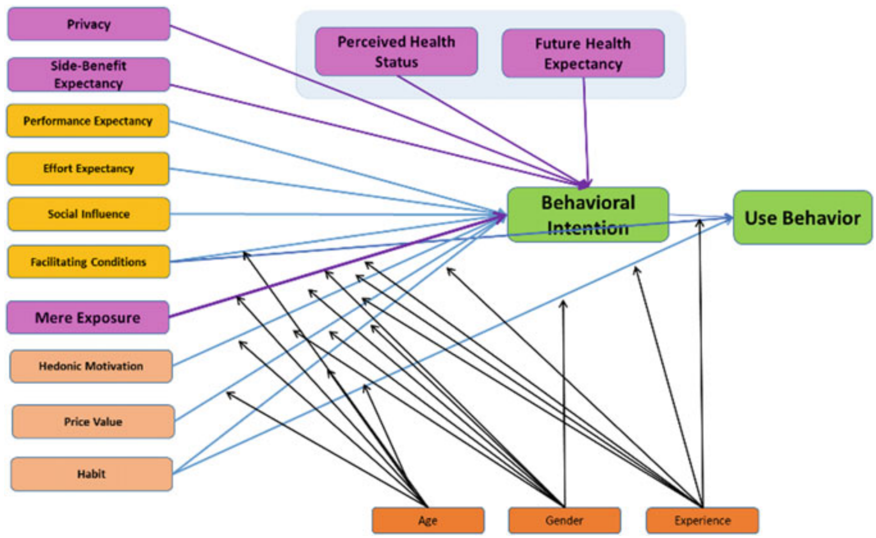

Fig. 5 Modified UTAUT2 model

the elimination of incomplete responses, remaining 366 responses were included in the analysis.

Below methods were used to reach survey participants:

- Personal network to reach known users of wearable devices
- User groups and fan pages of wearable devices on social media (mainly through Facebook)
- Reaching influencers on wearable devices (mainly through LinkedIn and Twitter)
- Using paid advertisements targeting wearable device users (mainly through Facebook and LinkedIn).

Demographic information about these 366 participants is summarized in below tables. Table 1 presents age group and gender distribution, and Table 2 presents countries where the participants are located. Most of the participants are from the

Table 1 Participant Qty. based on age and gender

Age group	Gender	
	Female	Male
18–24	19	14
25–34	76	53
35–44	67	40
45–54	38	15
>55	30	14
Total	230	136

Table 2 Participant Qty. based on country

Country	Participant quantity
USA	275
Turkey	47
Germany	16
Switzerland	8
Canada	5
UK	5
The Netherlands	2
Others	8
Total	366

USA, which can be due to high usage of social media and the success in social network advertisements targeting correct user groups. Countries marked as "Other" have only one participant who completed the survey. Number of female participants was higher than male participants in all age groups, which is an expected result for online surveys [36].

Below scale was used while preparing the results for analysis (Table 3):

- Questions with LIKERT scale were automatically converted to 1–5 scale.
- For gender, 0 is used for female, and 1 is used for male participants.
- For age, 1 is used for the youngest participant group, and 5 is used for oldest participant group.
- For experience, 1 is used for the minimum experience, and 5 is used for usage of more than 5 years.
  - Eight users who did not remember their usage duration were omitted from this analysis.

Survey items used by Venkatesh [9] were modified to suit the wearable device usage in health domain. These items and survey items for the newly proposed constructs are listed in Table 4. In addition to the items listed in Table 4, the survey

Table 3 Scale for analyzing survey results

Scale	Answers	Usage	Gender	Age	Experience
5	Strongly agree	Many times a day		>55	5 years or more
4	Agree	Often		45–54	3 years
3	Neither agree nor disagree	Sometimes		35–44	1 year
2	Disagree	Rarely		25–34	6 months
1	Strongly disagree	Never	Male	18–24	1 month
0			Female		

Table 4 Survey questions with new constructs

Performance expectancy	PE1. I find wearable mobile devices useful in my daily life to track health information
	PE2. Using wearable mobile devices increases my chances of achieving things that are important for my health
	PE3. Using wearable mobile devices helps me accomplish things more quickly
	PE4. Using wearable mobile devices increases my productivity
Effort expectancy	EE1. Learning how to use wearable mobile devices to track health information is easy for me
	EE2. My interaction with wearable mobile devices to track health information is clear and understandable
	EE3. I find wearable mobile devices easy to use
	EE4. It is easy for me to become skillful at using wearable mobile devices to track health information
Social influence	SI1. People who are important to me think that I should use wearable mobile devices to track health information
	SI2. People who influence my behavior think that I should use wearable mobile devices to track health information
	SI3. People whose opinions that I value prefer that I use wearable mobile devices to track health information
Facilitating conditions	FC1. I have the resources necessary to use wearable mobile devices to track health information
	FC2. I have the knowledge necessary to use wearable mobile devices to track health information
	FC3. Wearable mobile devices are compatible with other technologies I use
	FC4. I can get help from others when I have difficulties using wearable mobile devices to track health information
Hedonic motivation	HM1. Using wearable mobile devices to track health information is fun
	HM2. Using wearable mobile devices to track health information is enjoyable
	HM3. Using wearable mobile devices to track health information is very entertaining
Price	PV1. Wearable mobile devices to track health information are reasonably priced
	PV2. Wearable mobile devices to track health information are a good value for the money
	PV3. At the current price, wearable mobile devices to track health information provide a good value
Habit	HT1. The use of wearable mobile devices to track health information has become a habit for me

(continued)

Table 4 (continued)

	HT2. I am addicted to using wearable mobile devices to track health information
	HT3. I must use wearable mobile devices to track health information
	HT4. Using wearable mobile devices to track health information has become natural to me
Behavioral intention	BI1. I intend to continue using wearable mobile devices to track health information in the future
	BI2. I will always try to use wearable mobile devices to track health information in my daily life
	BI3. I plan to continue to use wearable mobile devices to track health information frequently
Use	Please choose your usage frequency for the wearable devices you own **Note**: Frequency ranged from "never" to "many times per day."
Privacy*	PRI1. My use of wearable mobile devices to track health information would cause me to lose control over the privacy of my information
	PRI2. Using wearable mobile devices to track health information would lead to a loss of privacy for me because my personal information could be used without my knowledge
	PRI3. Others (people or organizations) might take control of my information if I use wearable mobile devices to track health information
Side-benefit expectancy*	SBE1. Visual appearance of wearable mobile devices is important for me
	SBE2. Wearable mobile devices can be used as stylish accessories
	SBE3. Wearable devices used for tracking health information have many other useful functions
Future health expectancy*	FHE1. I feel healthy compared to one year ago
	FHE2. I will not have any major health problem in next 5 years
	FHE3. I have to take actions to stay healthy in next 5 years
Perceived health status*	PHS1. I have no problems doing my usual activities
	PHS2. I am not anxious or depressed
	PHS3. I feel healthy today
Mere exposure*	ME1. I know many people using wearable devices
	ME2. I have several friends using wearable devices to track their health status
	ME3. There are many people around me interested in wearable devices
	ME4. Number of people around me using or interested in wearable devices is increasing

Constructs and questions which were added in the proposed model are marked with an * also included questions regarding age, gender, experience with the technology, and location of the participant.

4.1 Analysis of Results

4.1.1 Criteria of Evaluation

After preparing the survey results for analysis, validity and reliability of the measurement model were examined, and then, the structural model was evaluated. The measurement model is explained as the relationship of indicator variables to their related constructs. Indicator variables are the questions for each construct and connected to their respective factors by the paths constructed in the model. The measurement model is also called as “Outer Model”.

Structural model, which is also called as “Inner Model”, is the relationship between latent variables. Latent variables are classified as exogenous and endogenous latent variables. Exogenous variables are defined as not being an effect of any other latent variable (there are no incoming arrows from other latent variables). A latent variable is endogenous if it is an effect of one or more other latent variables (there is at least one incoming arrow from other latent variables). In our models, BI and Use are endogenous latent variables, and others are exogenous latent variables. Table 5 shows important criteria for evaluating measurement and structural models with widely used limits for each criterion.

4.1.2 Measurement Model Analysis

This section uses output of Smart PLS 3 software PLS algorithm calculation. Results of the proposed model are listed for each step. PLS algorithm is run with path weighting scheme for maximum 1000 iterations and with stop criteria 10–7.

- Checking Convergence
  - The proposed model converged in seven iterations.
- Checking Reliability:
  - Cronbach’s alpha and composite reliability values are greater than 0.7 as expected, except 1 construct in the proposed model (SBE, which is also not very low).

  Table 6 shows the Cronbach’s alpha and composite reliability values.
  Checking Validity (AVE, discriminant validity, and HTMT)
- AVE is expected to be greater than 0.5 which is confirmed to be true.

Table 5 Evaluation criteria for measurement and structural models

	Criteria	Explanation
Measurement model criteria	Convergence	Iterations are expected to converge without reaching the maximum number of iterations
	Cronbach's alpha	Cronbach's alpha value is a good measure to estimate internal consistency and therefore reliability of the scale. Cronbach's alpha value greater than 0.7 assumes that all indicators of a construct are equally reliable [37, 38]
	Composite reliability	Composite reliability controls individual reliability of indicators and is expected to be greater than 0.7
	Convergent validity	Average variance extracted (AVE) should be greater than 0.5
	Divergent validity	Measured using Fornell Larcker criterion, square root of AVE is expected to be greater than correlation coefficient between structures
	HTMT	HTMT stands for heterotrait-monotrait ratio which is calculated as the ratio of geometric mean of heterotrait-heteromethod correlations and average of monotrait-heteromethod correlations HTMT is expected to be lower than 0.9 for a well-fitting model [39]
	Path loadings	Path loadings and cross-loadings should be checked to ensure internal consistency and discriminant validity
	Cross-loadings	High loading and low cross-loading values are expected. Path loadings are expected to be greater than 0.7

(continued)

Table 5 (continued)

	Criteria	Explanation
Structural model criteria	Structural path coefficients	Structural path coefficients show how factors are connected to other factors, and higher path coefficients mean stronger connection between latent variables
	Coefficient of determination (variance)	*R*-square is the overall effect size measure for structural model, which is also called as coefficient of determination. It is calculated only for endogenous latent variables. *R*-square will have a value between 0 and 1. A value near 1 indicates that most of the variation of the response data is explained, and a value near 0 indicates that the variation is explained very little by the input values [40]
	Multicollinearity (inner VIF)	Inner VIF values should be lower than 5 to ensure there is no multicollinearity between latent variables
	f-square (change in variance)	Change in *R*-square values when an exogenous latent variable is removed is called the f-square value f-square values are classified as small, medium, and high for 0.02, 0.15, and 0.35 [41]
	Residuals	Analyzing residuals can be used as a way to identify outliers in our result data Residuals greater than 1.96 imply outliers at the 0.05 significance level for a normally distributed data set

– Fornell Larcker criterion is used to test discriminant validity, which states square root of AVE (diagonal entries) to be greater than non-diagonal entries. This criterion is also confirmed.
– HTMT value is calculated and found to be lower than 0.9.

AVE and discriminant validity values are presented in Table 7. For each construct, diagonal entries are higher than the non-diagonal entries listed below the related construct.

HTMT values are calculated for the proposed model and presented in Table 8.

Table 6 CA and CR for proposed model

Proposed model		
	Cronbach's alpha	Composite reliability
BI	0.872	0.922
EE	0.861	0.906
FC	0.762	0.847
FHE	0.866	0.934
HM	0.881	0.927
Habit	0.774	0.846
ME	0.852	0.899
PE	0.76	0.848
PHS	0.762	0.855
Price	0.831	0.894
Privacy	0.889	0.911
SBE	0.61	0.767
SI	0.915	0.946
Use	1	1

- Checking Internal Consistency (Loadings)
  - High loading and low cross-loading is expected.
  - Results supported high loading and low cross-loadings.

Measurement model analysis confirms the healthiness of the model in terms of convergence, reliability, validity, internal consistency, and multicollinearity. Results of the proposed model are similar to the results of UTAUT2 model, and both are inside the generally accepted limits for partial least squares analysis [42].

4.1.3 Structural Model Analysis

After confirming the model to be valid and reliable according to measurement model analysis, structural model was analyzed using Smart PLS 3 Bootstrapping algorithm. In total, 1000 subsamples were produced using PLS Bootstrapping algorithm with a significance level of 0.05.

- Resulting path coefficients and R-square values are shown in below tables. Performances of both models were compared for endogenous latent variables, which are behavioral intention (BI) and use for the proposed model.

It is seen that, the proposed model provides a slight increase in predicting BI, but the value for predicting use behavior was the same for both models.

The R-square values and path coefficients for use were calculated and presented for both UTAUT2 and the proposed model in Table 9.

Table 7 Convergent and discriminant validity values for proposed model

Proposed model														
	AVE	BI	EE	FC	FHE	HM	Habit	ME	PE	PHS	Price	Privacy	SBE	SI	Use
BI	0.798	0.893													
EE	0.706	0.538	0.840												
FC	0.586	0.480	0.597	0.765											
FHE	0.877	0.149	0.195	0.149	0.936										
HM	0.809	0.533	0.494	0.439	0.138	0.900									
Habit	0.583	0.736	0.453	0.405	0.227	0.528	0.763								
ME	0.691	0.384	0.314	0.397	0.144	0.422	0.407	0.831							
PE	0.585	0.677	0.569	0.551	0.156	0.561	0.596	0.346	0.765						
PHS	0.666	0.296	0.362	0.256	0.445	0.318	0.268	0.190	0.309	0.816					
Price	0.739	0.292	0.317	0.326	0.168	0.398	0.308	0.267	0.327	0.171	0.860				
Privacy	0.773	−0.106	−0.106	−0.092	0.017	−0.033	−0.044	−0.028	−0.099	0.044	−0.107	0.879			
SBE	0.535	0.342	0.311	0.282	0.186	0.365	0.272	0.235	0.323	0.277	0.231	0.039	0.731		
SI	0.854	0.217	0.011	0.139	0.068	0.187	0.259	0.223	0.201	-0.028	0.226	0.083	0.103	0.924	
Use	1.000	0.478	0.337	0.343	0.026	0.366	0.460	0.280	0.372	0.220	0.133	−0.152	0.222	0.005	1.000

Table 8 HTMT values for proposed model

Proposed model	BI	EE	FC	FHE	HM	Habit	ME	PE	PHS	Price	Privacy	SBE	SI
EE	0.614												
FC	0.570	0.703											
FHE	0.164	0.223	0.175										
HM	0.607	0.559	0.520	0.159									
Habit	0.842	0.482	0.455	0.280	0.607								
ME	0.429	0.346	0.492	0.170	0.474	0.493							
PE	0.827	0.691	0.696	0.189	0.684	0.724	0.421						
PHS	0.334	0.421	0.297	0.519	0.364	0.302	0.201	0.388					
Price	0.319	0.354	0.411	0.211	0.430	0.352	0.295	0.388	0.186				
Privacy	0.099	0.103	0.087	0.057	0.045	0.078	0.041	0.078	0.062	0.110			
SBE	0.407	0.363	0.375	0.243	0.420	0.318	0.324	0.435	0.350	0.239	0.108		
SI	0.242	0.051	0.203	0.079	0.214	0.359	0.251	0.255	0.066	0.258	0.090	0.119	
Use	0.512	0.358	0.380	0.023	0.387	0.465	0.294	0.418	0.225	0.127	0.150	0.242	0.007

Table 9 Comparison for Use

Use		
	UTAUT2	Proposed model
R-square	0.267	0.267
Adj *R*-square	0.261	0.261
BI	0.253	0.253
FC	0.132	0.132
Habit	0.220	0.220

Table 10 Comparison for BI

BI		
	UTAUT2	Proposed model
R-square	0.647	0.657
Adj *R*-square	0.640	0.645
EE	0.123	0.112
FC	0.045	0.035
HM	0.057	0.032
Habit	0.470	0.473
PE	0.272	0.256
Price	−0.024	−0.031
SI	0.028	0.035
FHE		−0.062
ME		0.023
PHS		0.041
Privacy		−0.053
SBE		0.075

Similar to the comparison for use, Table 10 presents the *R*-square values and path coefficients for behavioral intention for both models.

Table 11 Inner VIF for proposed model

	BI	Use
BI		2.384
EE	2.022	
FC	1.848	1.309
FHE	1.300	
HM	1.910	
Habit	1.854	2.197
ME	1.384	
PE	2.189	
PHS	1.477	
Price	1.307	
Privacy	1.053	
SBE	1.244	
SI	1.196	

- Checking Multicollinearity
  - Multicollinearity exists if two or more independent variables are highly correlated, variance inflation factor (VIF) is used to test multicollinearity.
  - Inner VIF values are calculated in this step, the VIF values were lower than 5, stating that there is no multicollinearity for the inner model also.

  Inner VIF values for behavioral intention and Use are presented in Table 11.
  Checking f-square
- f-square measures the strength of each predictor variable in explaining the endogenous variables.
  - The ranges 0.02, 0.15, and 0.35 are considered as weak, moderate, and substantial, respectively (Chin 1998). f-square can also be defined as the difference in *R*-square when a specific construct is removed from the model.
  - It is calculated by Smart PLS for the endogenous variables, which are BI and use in our case.

  The f-square values for the proposed model are presented in Table 12.

4.2 User Group Analysis

We conducted a further analysis based on various user groups that are identified by gender, age, and experience (duration of wearable device usage) attributes. Data is separated into six subsets for user group analysis. The participant numbers in each group and a basic description of the groups is presented in Table 13.

Table 12 f-square values proposed model

Proposed model	
	Sample mean (M)
BI → Use	0.040
EE → BI	0.024
FC → BI	0.007
FC → Use	0.024
FHE → BI	0.011
HM → BI	0.005
Habit → BI	0.363
Habit → Use	0.036
ME → BI	0.004
PE → BI	0.089
PHS → BI	0.007
Price → BI	0.005
Privacy → BI	0.014
SBE → BI	0.018
SI → BI	0.006

Table 13 User groups for 366 participants

Group name	Group information
Age 1–2 (young)	162 participants (between 18 and 34 years)
Age 4–5 (old)	97 participants (over 45 years)
Exp 1–2 (short term)	106 participants (up to 6 months usage)
Exp 4–5 (long term)	128 participants (3 years and more usage)
Female	230 participants
Male	136 participants

For user group analysis, first, we removed the least significant paths (paths with coefficients less than 0.05) from both models and reran both models and saw that R^2 decreased by less than 1 percent. For the sake of simplicity, we used both models with reduced paths while doing the user group analysis. The least significant paths are highlighted in bold Table 14.

After the removal of insignificant paths, structural analysis calculation was done for user groups based on gender, age, and experience. Although the path coefficient between HM-BI is lower than 0.05 for the proposed model, it was higher than 0.05 for the UTAUT2 model and not removed from the model in order to make a comparison between the models, which was presented in Table 15 at the end of this section. Figure 6 presents the updated models after eliminating the insignificant paths.

Table 14 Proposed model

Proposed Model		
	BI	Use
BI		0.253
EE	0.112	
FC	**0.035**	0.132
FHE	−0.062	
HM	0.032	
Habit	0.473	0.220
ME	**0.023**	
PE	0.256	
PHS	**0.041**	
Price	**−0.031**	
Privacy	−0.053	
SBE	**0.075**	
SI	0.035	

Paths FC-BI, Price-BI, SI-BI, ME-BI, and PHS-BI were removed from the proposed model. This caused the removal of price, social influence, mere exposure, and perceived health status constructs from the model. Although these constructs are not included in the user group-based analysis, their effect is also discussed in the following sections. Analysis according to user groups was done with these simplified models. Path coefficients for the proposed model after deleting the insignificant paths for all 366 participants are presented in Fig. 7.

4.2.1 Age Group-Based Comparison

This study contains data from 366 participants whose ages lie in the range 18 and 65. Participants with age 35 or below were labeled as young users, and participants with age 45 and above were labeled as old users. Participants between 35 and 44 years were omitted from the analysis to achieve a clearer division between these two user groups. Figure 8 shows the path coefficients for the younger users, and Fig. 9 shows the path coefficients for the older users, based on above classification.

The proposed model shows a stronger relation for habit on use for older (Habit → Use = 0.395) users compared to younger (Habit → Use = 0.183) users. This finding is in line with a previous study on older users' acceptance of Internet banking, in which habit was found to be an important factor of use behavior [43]. On the other hand, performance expectancy was found to be more important for younger (PE → BI = 0.298) users than older (PE → BI = 0.117) users. This shows us that, two most important factors (Habit and PE) on adoption of wearable devices are significantly influenced by age. Additionally, it was found that facilitating conditions have a stronger link with use for younger users (FC → Use = 0.192) compared to older

Table 15 Comparison of user groups

	Participant Qty.	366	162	97	106	128	230	136
Model	Path	All	Young	Old	New user	Experienced	Female	Male
UTAUT2	**BI (*R*-square)**	**0.644**	**0.680**	**0.579**	**0.659**	**0.685**	**0.609**	**0.719**
UTAUT2	**Use (*R*-square)**	**0.268**	**0.225**	**0.331**	**0.296**	**0.175**	**0.183**	**0.384**
UTAUT2	BI → Use	0.253	0.183	0.171	0.087	0.277	0.129	0.435
UTAUT2	FC → Use	0.135	0.192	0.089	0.127	0.065	0.172	−0.003
UTAUT2	Habit → Use	0.220	0.183	0.395	0.411	0.123	0.230	0.227
UTAUT2	EE → BI	0.132	0.125	0.149	0.158	0.103	0.140	0.107
UTAUT2	HM → BI	0.057	0.040	0.108	−0.021	0.176	0.133	−0.013
UTAUT2	Habit → BI	0.475	0.472	0.540	0.479	0.436	0.510	0.403
UTAUT2	PE → BI	0.286	0.298	0.117	0.331	0.249	0.150	0.470
Proposed model	**BI (*R*-square)**	**0.653**	**0.695**	**0.594**	**0.662**	**0.697**	**0.621**	**0.728**
Proposed model	**Use (*R*-square)**	**0.268**	**0.225**	**0.331**	**0.296**	**0.175**	**0.183**	**0.384**
Proposed model	BI → Use	0.253	0.183	0.170	0.087	0.277	0.130	0.435
Proposed model	FC → Use	0.135	0.192	0.089	0.127	0.065	0.172	−0.003
Proposed model	Habit → Use	0.220	0.183	0.395	0.411	0.123	0.229	0.227
Proposed model	EE → BI	0.123	0.113	0.149	0.137	0.094	0.118	0.093
Proposed model	FHE → BI	−0.047	−0.026	−0.076	0.023	−0.100	−0.044	−0.013
Proposed model	HM → BI	0.040	0.032	0.085	−0.015	0.157	0.121	−0.031
Proposed model	Habit → BI	0.483	0.476	0.550	0.473	0.458	0.526	0.398
Proposed model	PE → BI	0.272	0.262	0.097	0.317	0.241	0.139	0.447
Proposed model	Privacy → BI	−0.046	−0.063	−0.046	−0.037	−0.023	−0.094	0.052
Proposed model	SBE → BI	0.080	0.117	0.096	0.037	0.069	0.058	0.105

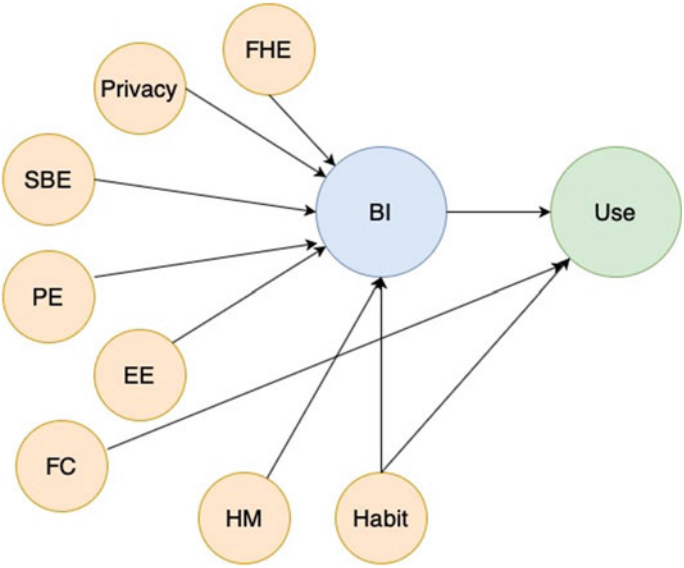

Fig. 6 Proposed model (insignificant paths removed for simplicity)

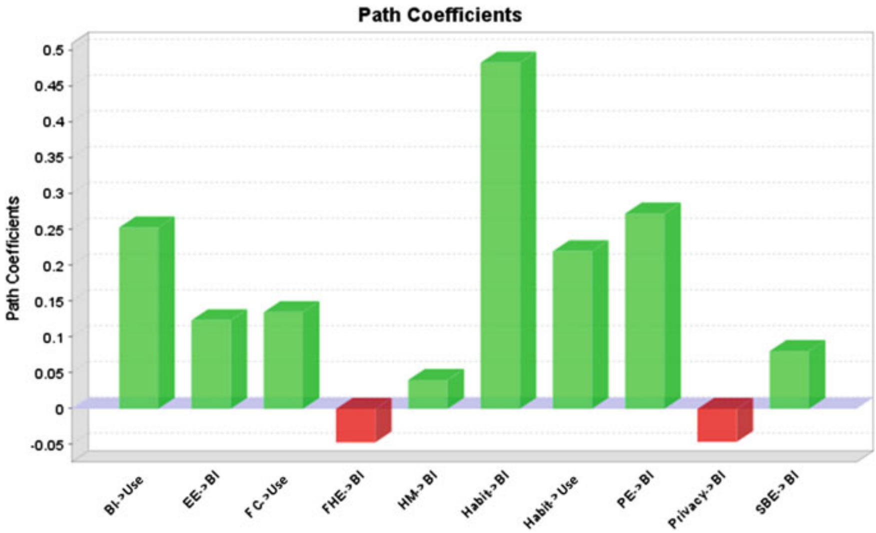

Fig. 7 Proposed model (for all participants)

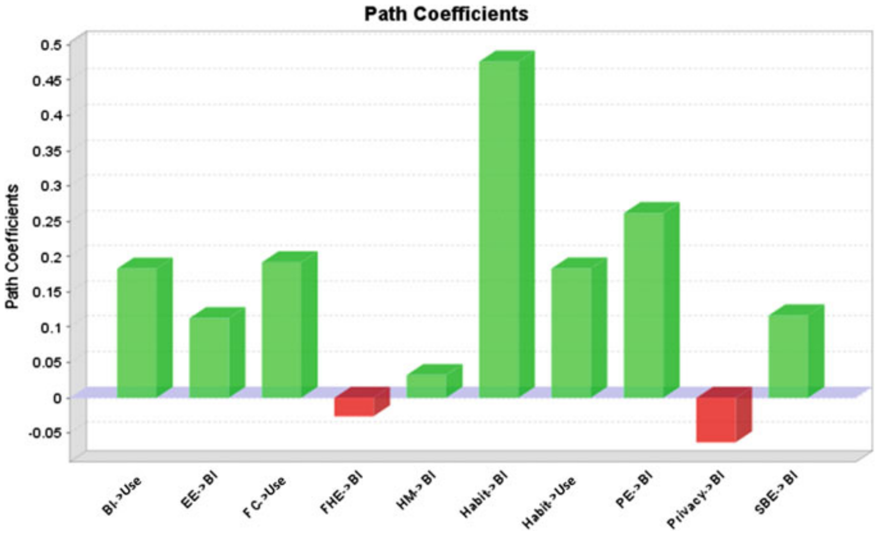

Fig. 8 Proposed model (for young users)

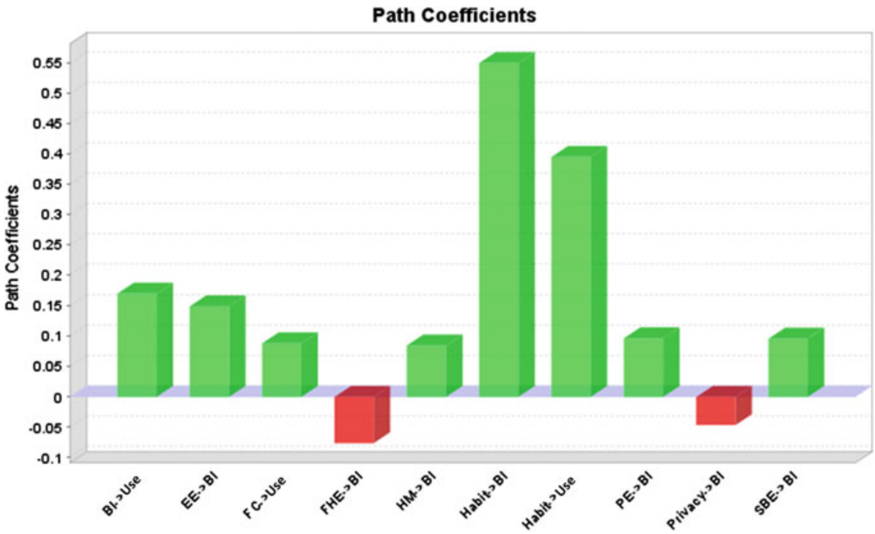

Fig. 9 Proposed model (for older users)

users (FC $\rightarrow$ Use $=$ 0.89). As we expect younger users to be more tech-savvy, this finding is somewhat counter-intuitive and requires further analysis.

Other parameters did not lead to a significant difference between user groups.

- For both models, FC-Use almost halved (0.192–0.89) from younger to older.

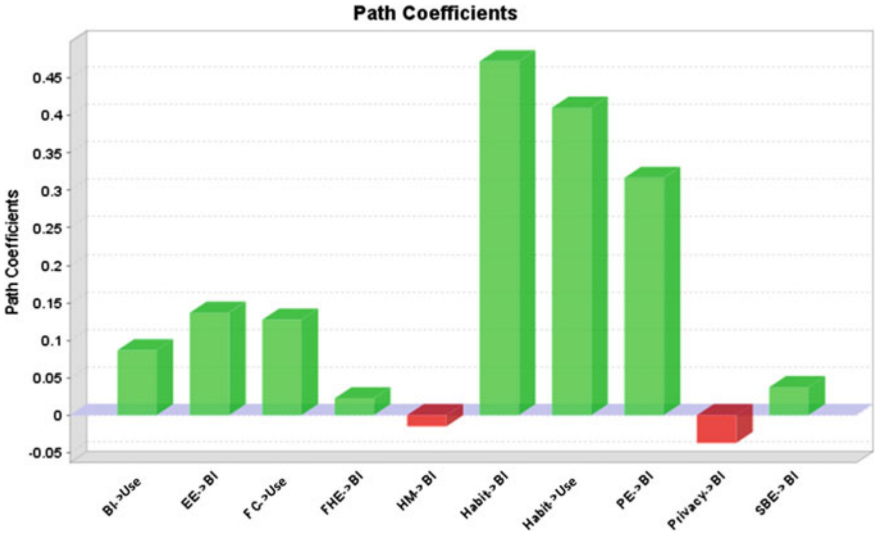

Fig. 10 Proposed model (for new users)

- For both models, Habit-Use almost doubled (0.183–0.265) from younger to older.
- For both models, PE-BI decreased more than half from younger to older.

4.2.2 Usage Duration-Based Comparison

Users were classified based on their experience with the technology. One hundred and six participants who have been using wearable devices for 6 months or less were classified as new users. One hundred and twenty-eight participants who have been using wearable devices for 3 years or more were classified as experienced users. New users had a weaker connection between behavioral intention and use (BI → Use) compared to experienced users with an increase of more than two times (0.087–0.277). As expected, facilitating conditions are less important for experienced users. The relationships between facilitating conditions and use are halved from new users to experienced users. Figures 10 and 11 show the path coefficients for new and experienced users, respectively, based on usage duration and experience with the technology.

4.2.3 Gender-Based Comparison

Among 366 participants, 230 were female, and 136 were male. Figures 12 and 13 present the differences between female and male users according to the proposed model.

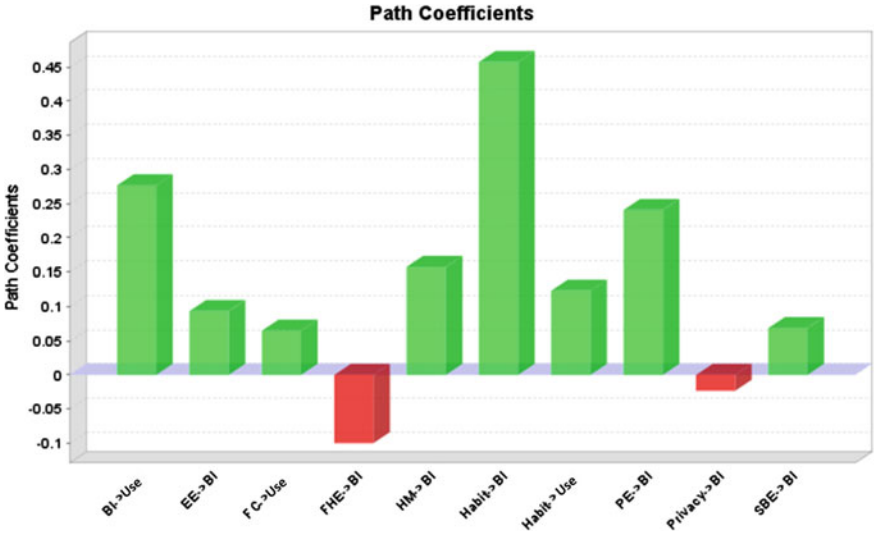

Fig. 11 Proposed model (for experienced users)

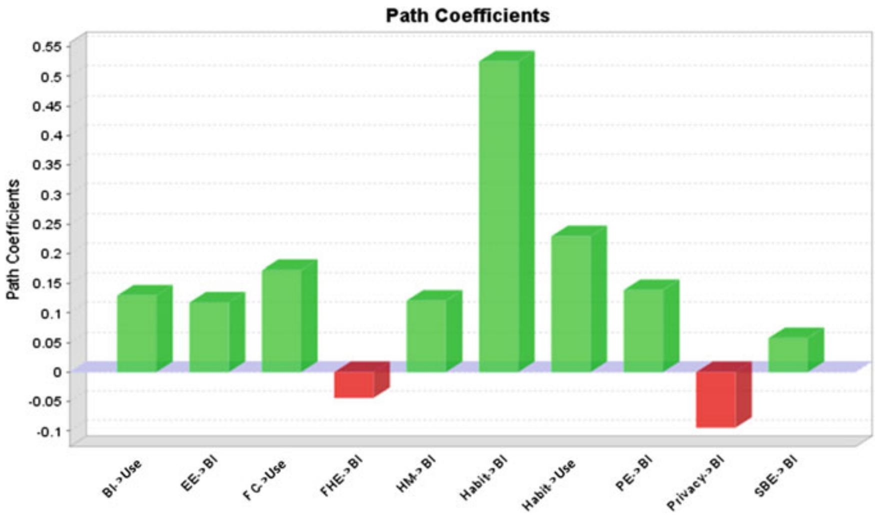

Fig. 12 Proposed model (for female users)

The R^2 value for behavioral intention is slightly higher (around 15%) for male users, and R^2 value for actual usage is a lot higher (almost 2 times) for male users compared to female users. This difference in R^2 values based on gender is clearly visible in the proposed model. The relationship between behavioral intention and use (BI → Use 0.13 for females and 0.435 for males) and the relationship between

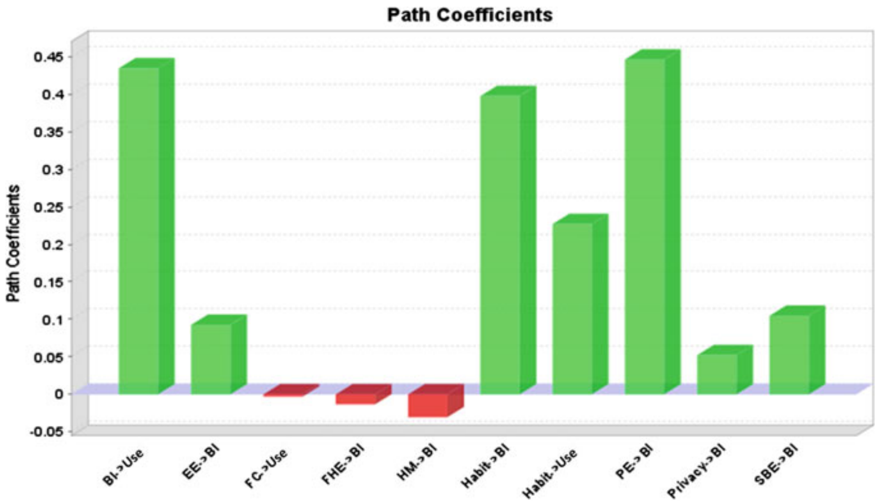

Fig. 13 Proposed model (for male users)

performance expectancy and behavioral intention (PE → BI) is almost tripled for male users compared to female users (0.150 for females and 0.47 for males). It is clear that both models perform significantly better for male users.

Table 15 presents a summary of path coefficients and *R*-square values for both models for all 366 participants as well as the six user groups explained above.

It is seen that not only *R*-square values significantly vary among different user groups but also the influence of each construct on behavioral intention (BI) and use is different for each user group. These findings are further explained in Sect. 5.

4.3 Open-Ended Questions

In total, 50 participants completed the survey with open-ended questions. The aim of the open-ended questions was to understand the main reason of wearable device usage. The participants were not only asked about their own opinion and experience but also about their perception on why their friends use or do not use these devices. Answers to these questions were grouped, and the mostly given answers were listed in the below table. Table 16 shows these questions and corresponding mostly given answers.

The survey showed that participants think that cost is the most important reason preventing their friends from using wearable devices, but very few (only 3) mentioned cost as the most negative aspect of their devices. The reason for this could be related to the one-time payment nature of these devices, especially for the long-term users, the importance of cost seems to fade away [44]. Participants reported battery/charging as the most negative aspect of wearable devices. Wearable devices are becoming part of

Table 16 Open-end questions and answers

	Question	Mostly given answers
1	What is the main purpose of using your wearable device?	Track physical activity Increase physical activity Track sleeping Track heart rate Easy access to phone Track daily workouts Set reminders Track steps
2	What is the main benefit you get from your wearable device?	Sleep pattern Being healthy Being multipurpose (track activity, integrate with phone, reminders) Motivate to walk more Check heart rate
3	Considering your friends who are using wearable devices. What may be their main reason to use wearable devices?	Being healthy Tracking steps Lose weight Ease of use Being trendy
4	Considering your friends who are not using wearable devices. What may be their main reason for not using wearable devices?	Price/being expensive Do not make exercise Privacy
5	What can you do motivate your friends to use wearable devices?	Show them my results Explain them how to use Give incentives Promote health
6	What is the most negative aspect of wearable devices?	Battery/charging Accuracy Outdated too quickly Cost Not very fashionable/stylish Privacy

users' daily routine, and users rely on many services provided by these devices such as receiving notifications, checking step count, sleep duration or even just checking the time more and more. Any interruption to these services leads to significant discontent. When the participants were asked about the main purpose of their wearable device usage, most of the participants stated "tracking" as the main reason. Some are using wearable devices to track daily physical activity and exercises, whereas others are tracking sleep duration and heart rate. Tracking proves to be useful only after a relatively longer and consistent usage, and this aspect explains the strong performance of habit construct in the quantitative analysis.

5 Interpretation of Results

Results of measurement and structural model were analyzed in detail and explained in above sections. Measurement model analysis confirms the healthiness of the model in terms of convergence, reliability, validity, internal consistency, and multicollinearity. Results of the proposed model are inside the generally accepted limits for partial least squares analysis. How much of the variance in behavioral intention and use can be explained using these models is the main criteria for evaluating model performance. Models with high R^2 provide a precise prediction [45], and R^2 values up to 0.25 are considered weak, R^2 values up to 0.50 are considered moderate, and values up to 0.75 are considered as substantial [42]. It is seen that proposed model explained substantial variance of behavioral intention ($R^2 = 0.657$). The model explained moderate variance of use behavior ($R^2 = 0.267$). These results show that proposed model can be used in the domain of wearable devices, but the newly proposed constructs did not provide any significant added value regarding the explanatory power of the model. An in-depth analysis of the survey data pointed to an issue in the measurement of "Use" construct. It was seen that 323 of 366 participants answered this question with 4 (often) and 5 (many times a day). It is likely that having almost a constant distribution negatively influenced the prediction of "Use" construct. Original UTAUT2 survey asks users the frequency of their use of a technology, which can be answered based on how often that specific technology is used. In our survey, the same question was used. With hindsight, it is seen that the question used in original UTAUT2 study could not adequately reflect the use of technology in case of wearable devices because it does not differentiate between active and passive usage. Using a wearable device to track health information is a continuous activity, and wearing that device and controlling the data collected by the sensors and taking actions based on the feedback of the device are different things. The addition of new questions for better addressing the nature of wearable device usage is likely to improve the model performance for wearable devices.

In a previous research on adoption of Internet banking, habit was found to be a stronger predictor of behavioral intention to use [43]. Our research also shows that habit is a strong determinant of technology adoption. Furthermore, our research shows that especially for older users the habit-use intention relation is significantly stronger. In addition to habit, we also found that performance expectancy is a very strong predictor of behavioral intention to use wearable devices for health status tracking. Habit and performance expectancy are by far the most dominant factors influencing behavioral intention to use, and hence, further breakdown of these factors may provide better insights and improve the success of proposed model.

The answers to open-ended questions emphasize the importance of price; however, quantitative analysis of the model shows that price has a very low impact (path coefficient less than 0.03) on behavioral intention to use wearable devices. It seems that once the wearable device is acquired, it does not have any significant impact on the use frequency. In a similar way, the answers to open-ended questions indicate to battery/charging problem but neither original UTAUT2 constructs nor any of the newly proposed constructs is able to detect this factor. Current technology adoption models and theories do not include effect of batteries and charging to users' adoption of wearable devices [46]. Observations from the open-ended questions regarding price and battery/charging are important factors which cannot be addressed with existing constructs. This indicates the importance of hybrid approaches in technology acceptance studies which supports the findings from quantitative analysis with qualitative data from interviews or open-ended questions.

The effect of performance expectancy (PE) on behavioral intention (BI) was found to be more important for males, in a study on electronic document management systems, since males are more result-oriented than females [47], and our study confirms this finding for adoption of wearable devices. BI-Use and PE-BI have a stronger relation for male users compared to female users.

Our study also shows that impact of social influence to behavioral intention to use technology and impact of price to behavioral intention (BI) is stronger for older users compared to young users. On the other hand, performance expectancy seems to be much more important for young users in comparison with older users as seen from PE-BI relation.

Habit-Use has a weaker relation for experienced users compared to new users, whereas relation between BI-Use is stronger for experienced users in comparison with new users. However, BI-Use relation needs a further study with a focus on use type (active, passive) as explained above.

It is seen that social influence which is defined as the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology [8] is not a very important factor on the use of wearable devices for health purposes.

Facilitating conditions, which are defined as consumers' perceptions of the resources and support available to perform a behavior [9], seem to be influential on the use of the wearable devices, but interestingly, it has less impact on the behavioral intention to use wearable devices. Our study shows a weaker FC-Use relation for male users compared to female users, which is in compliance with previous findings [47]. Furthermore, as expected, facilitating conditions were found to be less important for experienced users.

Side-benefit expectancy (in our case, wearable device's being fashionable and stylish) is found to be the most important fourth factor after performance expectancy, effort expectancy, and habit. However, its influence is significantly lower in comparison with other better performing three constructs. It is also seen that SBE is relatively more important for younger users compared to other groups.

Neither the quantitative analysis nor the open-ended questions show that privacy is an important factor for the wearable device users. It is very likely that, this result is due to the fact that most of the users who participated in the study use fitness trackers and smartwatches and the data collected by these devices seems to be less important in regard to privacy. In case of some other devices (fertility trackers and neurological monitors), privacy may emerge as an important factor.

An interesting finding of the overall study is that moderating effects such as gender, age, and experience affect almost all factors. Furthermore, it is also seen that proposed model performance is significantly higher for male users compared to female users.

6 Conclusion

This study proposed some new generic and domain-specific constructs in addition to original UTAUT2 constructs and empirically tested both models in mobile health domain, in order to understand factors affecting consumers' adoption of wearable devices for health status tracking. The results were analyzed both to verify the model fitness and to see how the effect of each construct differs for different user groups based on moderating factors age, gender, and experience with technology. User group-based comparison of path coefficients showed that factors affecting acceptance of wearable devices usage vary significantly depending on age, gender, and experience (duration of wearable device usage). Results from the analysis showed that proposed model could be used as a tool to analyze factors affecting technology adoption of consumers. However, it is also seen that there is a room for improvement. This work is part of a broader study and will be extended with new quantitative analyses and interviews in order to collect deeper insights from consumers of wearable devices. All research studies have some limitations, and our work is not an exception. On the one hand, wearable device users who are not active in social media might be underrepresented in our study due to the fact that social media was the main element to reach survey participants. On the other hand, there are many different wearable devices in the market collecting various health information, and it turned out that most of our survey participants use fitness trackers and smartwatches. This might limit the explanatory power of our study to these devices. Reaching the users of innovative high-tech wearables which do not have a significant market share yet is a challenging target for our future work.

Finally, conducting interviews with different user groups is likely to bring additional value to this study by enhancing quantitative findings from the survey.

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Enablers for IoT Regarding Wearable Medical Devices to Support Healthy Living: The Five Facets

Mustafa Degerli and Sevgi Ozkan Yildirim

1 Introduction

Currently, multiple applications in business, manufacturing, home, healthcare, and knowledge management, utilizing the Internet of Things (IoT) have increased intensely, and the health care is the prominent application area in the top ones of the pertinent list [1]. Owing to notable developments in low-power wireless network technologies and the IPv6, every object grows into the part of the IoT by means of the Internet. Additionally, wearables, body sensor networks, ambient, and IoT technologies are recently quite popular in health-related research and practices. Wearable technologies are a principal piece of the IoT. While there are remarkably mature wearable and IoT technologies, there are still numerous prominent challenges shaping their acceptance and use [2].

Besides, as people are more aware and/or afraid of their health and well-being, wearable devices for such means become more prevalent. There is always a need for studies to improve the size and compatibility of such devices [3]. It can be said that the current practices of the IoT concept to health services are still in its quite early stages, and a patient-centered method is vital for success [4]. A review study concluded that home was the most popular place for medical IoT applications and there are several notable IoT applications based on wearables [5].

Moreover, we see that the IoT is one of the most hopeful technologies for the near future, and in this context, our healthcare and well-being are going to be obtaining huge assistance thanks to them. It was noted that additional studies are significant for

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_10

developing present techniques and practices of the IoT to overcome the challenges [6]. Luckily, through IoT devices, we are able to have resourceful utilization of the pertinent technology and improved modernization for healthcare contexts [7].

Headed predominantly for improving the quality of life for everybody, technology is there as a significant tool. For a thoroughly independent, strong, and healthy living, technology is admiringly there to be utilized. In this context, the application of information technologies like wearables is going to intensely change and shape our present and upcoming healthcare interpretations and practices [8, 9]. Wearable medical devices are the instruments, which principally offer medical monitoring and support, those people wear particularly to both manage and improve their health. Precisely, the leading instances of these devices are smartwatches, smart clothes, smart glasses, sports/activity trackers, or various sensors placed on bodies [10, 11].

The main objective of this chapter is to describe and discuss the enablers for IoT regarding wearable medical devices. Explicitly, comprehensive particulars for the enablers and relevant characteristics to attain, sustain, and improve the success of IoT regarding wearable medical devices are provided.

The main contribution of this chapter is to add to the pertinent body of knowledge concerning the enablers for IoT regarding wearable medical devices to support healthy living with extracted results. This contribution advances the relevant understanding and is going to be helpful for researchers in the field and wearable medical devices product developers.

Regarding the results of this study, mainly, there are five enablers with 17 items for success. The identified enablers in order with respect to their degree of impacts are dependability; design; worthiness; privacy, confidentiality, and security; and compatibility. Furthermore, a novel checklist was crafted for stakeholders to appraise the relevant devices and identify main points to improve their products and services.

2 Wearable Medical Devices

Wearable medical devices are autonomous and noninvasive, and they perform the main medical functions of monitoring and/or support. Furthermore, these devices are supported by the human body or clothing [12]. Smartwatches are the chief spread among wearables [13–15]. For integrated care, investments in information and communication technologies are an inevitability [16]. There are also assistive technologies to support health [17]. The foremost importunity of assistive health technology is on the way to sustain and advance people's functioning and well-being [18].

Wearables are becoming more omnipresent, and they have numerous aids for life [19–21]. Efficient and viable wearable devices are going to lead to positive changes for not only individuals but also societies at large [22]. Wearable medical devices come up with boundless prospects and noteworthy upcoming for healthcare settings [23], and they provide remarkable means for reducing the burden on systems and costs associated with health care owing to aging society [24]. Moreover, wearable medical devices are one of the most practical approaches to take protective health monitoring and to treat patients with a legitimately custom-made method at an early stage to advance early detection, early diagnosis, and early treatment [25].

Wearable medical devices with a variety of sensors are and will be used for a wide range of healthcare drives [26]. Owing to wearable medical devices, pervasive monitoring, transmission, and storage of data become more in real world [27]. Now, it is clear that wearable medical devices are pragmatic and clinically useful for diagnosis, treatment, and care [28–30].

It is definitely projected that there will be various additional user-acceptable, high-performance, and low-cost wearable devices that will be presented for recognition of a variety of physical activities [31, 32]. Furthermore, there is a striking rising in medical devices to control bodily functions and to measure certain physiological parameters [33]. Technology maturity level for home health monitoring technologies is still moderately low [34], yet wearable technology usage is projected to increase constantly [35]. For sure, a transdisciplinary approach will move us rapidly forward on this journey [36–38].

Healthy aging can be defined as the course of developing and sustaining the functional ability that empowers well-being in older ages, where functional ability encompasses the health-related attributes that qualify people to be and to do what they have reason to value. Physical activity and nutrition are the foremost aspects prompting healthy aging [18]. Furthermore, older people are more likely to have more advantages in using wearable medical devices regarding the early detection and management of situations related to their health [39–43].

The essence of healthy aging is the functional ability comprising the intrinsic capacities of people, relevant environmental characteristics, and interactions between people and these [44]. Healthy aging is the concentration of the World Health Organization's work on the subject of aging between 2015 and 2030 [45]. Healthy aging is a course that occurs across the life course rather than as a state at a particular point in time [46]. Active aging is the progression of enhancing prospects for health, participation, and security with the intention of improving quality of life as people age [47]. For active aging, investigating digital strategies embodies a thrilling zone of global research [48]. Active aging is the process of heightening prospects for health, participation, and security with the aim of boosting the quality of life as we age [18]. Physical activity is a leading aspect of both health and well-being [49]. Regular physical activity is very imperative for healthy aging, and luckily technology devices such as wearables are practically there to encourage people for regular physical activity [50–54].

Aging in place is the term where people safely and comfortably pursue their independent and high-caliber life at their own home and community. This, of course, diminishes the possible associated costs of external supports for health and well-being [55]. New technological and innovative devices will be beneficial for tracking significant parameters to impeccably deliver preventive and proactive actions for health. Therefore, caring for people in their own homes thanks to technology devices possibly will be effective and economically adventurous [55]. To manage mobility loss of people, physical activity including physical exercise requiring energy expenditure is a must [56]. By way of active aging and physical activity, we will more possibly be able to avoid, slow, or converse deteriorations on the subject of people's physical and mental capabilities [56].

The World Health Organization recommends that health systems ought to be oriented around intrinsic capacity and functional ability, and in this context, we need to employ technologies (like wearable medical devices) in clinical, home, and community settings [57].

Today, wearable technologies are becoming more pervasive. Besides, wearable medical devices are promising instruments for healthy living and aging for today and the future. For these reasons, it is very important to align these health-related technologies with people's needs and expectations. People's acceptance, adoption, and intention of the use of wearable medical devices are anticipated to grow in the near future [58], and the market for wearable medical devices is one of the wildest rising ones of this era [59].

Smart wearable systems designed for health monitoring are deeply in the interest zone of not only researchers but also industry professionals [60]. The success of innovative technologies like wearables by people is a vital issue not only for governments and healthcare providers but also for technology providers and other key actors regarding people's life [61]. Parenthetically, unlike typical technologies like smartphones, the adoption of wearable medical devices has been moderately slow. Thus, there is an increasing concentration to comprehend the full picture [62, 63].

3 Relevant Studies

While it is still open for firm improvements, there are some distinguished efforts. In a relevant research study [64], researchers concluded the importance of perceived security. In another research work [65], researchers highlighted the significance of effective quality, relative advantage, and availability. Moreover, in another study effort [58], researchers verified the prominence of perceived risk and compatibility constructs. In notable research [29], it was shown that people's choices to adopt healthcare wearable devices are determined by their risk–benefit analyses, and perceived privacy risk is important. In an additional related study [66], scholars showed the importance of technical attributes.

Furthermore, in one more remarkable study [67], scholars confirmed that perceived value is a solid factor. Besides, people's privacy concerns were shown to be significant in pertinent research [68]. Another relevant study [69] determined that privacy protection and readability are salient constructs for success. Above and beyond, in another notable study [70], it was concluded that such devices must be useful, noninvasive, aesthetically pleasing, comfortable, durable, reasonably priced, easy to care for, and capable of protecting the privacy of users to attain the success.

Concerning all these realities, drives, and promises, the principal objective of this work is to identify critical enablers for IoT regarding wearable medical devices.

Unambiguously, we essentially aimed to identify relevant enablers and pertinent characteristics to attain, sustain, and heighten the success.

4 Study Design and Methodology

4.1 The Questionnaire

A thoughtfully original questionnaire was developed and deployed in the study. Both the reliability (reliability test) and content validity (expert views) were ensured for the questionnaire developed and used. Openly, Cronbach's alpha value was calculated with IBM SPSS and 0.861 value was gotten, which is above the minimum requirements (0.6–0.7) [71–73]. Furthermore, expert reviews done in this context purposefully maintained the validity of the questionnaire employed [71–73].

Moreover, in advance of applying the questionnaire to collect data, the Middle East Technical University's Human Subjects Ethics Committee review and approval were fully satisfied.

4.2 The Sample

By using the questionnaire, a rich and original data set was collected from 511 people who are real and existing wearable medical device users to draw conclusions, ensuring informed consent. As can be seen in Tables 1 and 2, the collected data set is all-inclusive to draw fairly dependable conclusions.

4.3 Method

With the purpose of exploring and reviewing the causal and principal correlational relations in the collected data set, an exploratory factor analysis [74] was applied with IBM SPSS 23.

In this context, first of all, the sample size adequacy was checked and ensured. As data collected from 511 people, this research met the sample size requirement far above the recommended minimum values (170–200) [73, 75–77].

After this, the anti-image correlation matrix was analyzed to test whether correlations among the individual items are strong enough for ensuring that the correlation matrix is factorable [78], and it was seen that this condition requiring all related values must be greater than 0.5 which was also met satisfactorily (Table 3).

Moreover, Kaiser-Meier-Olkin (KMO) and Bartlett's tests were applied, and extracted relevant commonalities were handled. For relevant factor analysis, the

Table 1 Particular frequencies of the sample

Gender	**N**	**%**	**Education**	**N**	**%**
Women	254	49.7	Prim. Edu.	4	0.8
Men	257	50.3	High Sch.	93	18.2
			Bachelor	228	44.6
Generation	**N**	**%**	Master's	145	28.4
Gen Z	100	19.6	Doctorate	41	8.0
Millennials	223	45.6			
Gen X	116	22.7	**BMI Cat.**	**N**	**%**
Boomers	62	12.1	Underweight	20	3.9
			Normal	345	67.5
Income	**N**	**%**	Obesity	25	4.9
Low	214	41.9	Overweight	121	23.7
Mid	200	39.1	Sample Size = 511		
High	97	19.0			

Table 2 Frequencies regarding wearable medical devices used by participants

Wearable medical devices used by the participants	N	%
Smart clothes	6	1.2
Smart glass	7	1.4
Body sensor(s)	28	5.5
Sports/activity tracker	198	38.7
Smartwatch	392	76.7

Table 3 Anti-image correlation values

Item	Value	Item	Value	Item	Value
DPD1	0.898	DES4	0.773	PCS1	0.826
DPD2	0.874	DES5	0.784	PCS2	0.839
DPD3	0.844	WOR1	0.794	PCS3	0.823
DPD4	0.864	WOR2	0.761	CMP1	0.818
DES1	0.825	WOR3	0.861	CMP2	0.824
DES3	0.782			CMP3	0.805

KMO sampling adequacy value of 0.6 or above and Bartlett's test significance value of 0.05 or less are required [73, 79]. For our work, the KMO value is 0.825, and Bartlett's test significance is 0.000, meeting the requirements (Table 4).

Additionally, values for the items regarding extracted communalities ought to be bigger than 0.40 [80], and this condition was also met in our study as these values ranged from 0.606 to 0.897 for the 17 items (Table 5).

Table 4 KMO and Bartlett's test results

Kaiser-Meyer-Olkin measure of sampling adequacy		0.825
Bartlett's test of sphericity	Approx. Chi-Square	4809.472
	df	136
	Sig.	0.000

Table 5 Communalities

	Initial	Extraction		Initial	Extraction
DPD1	1.000	0.680	WOR2	1.000	0.897
DPD2	1.000	0.787	WOR3	1.000	0.809
DPD3	1.000	0.769	PCS1	1.000	0.785
DPD4	1.000	0.759	PCS2	1.000	0.785
DES1	1.000	0.655	PCS3	1.000	0.798
DES3	1.000	0.606	CMP1	1.000	0.749
DES4	1.000	0.745	CMP2	1.000	0.699
DES5	1.000	0.683	CMP3	1.000	0.740
WOR1	1.000	0.858			

Furthermore, the method for factor analysis extraction and the method for rotation were settled. In our work, the principal components method as the most frequently used one was used to reduce data to a set of factor scores, and as the best orthogonal rotation, varimax was set [73, 79, 81, 82].

Besides, we checked item main loadings (coefficients) and created the rotated component matrix where item main loadings whose absolute values lower than 0.4 were suppressed in the factor construction to make it more comprehensible [73]. The rotated component matrix with item loadings is given in Table 6.

Consequently, we determined the number of factors and evaluated the pertinent total variance explained. In this context, we used the Kaiser criterion on the way to determine the ideal number of factors [79], and five was determined (Fig. 1).

Moreover, the total variance explained by the identified five enablers through 17 characteristics was calculated as 75.318%, which is greater than the recommended 50% value [83]. The total variance explained values are given in Table 7.

Consequently, the enablers (factors) and characteristics (items for each factor) were defined and analyzed. By principle, three items for every factor are sufficient for identification of the factor [84, 85], and for our work, this recommendation was also fully met as there are at least three items per factor in our study.

Table 6 Rotated component matrix

	1	2	3	4	5
DPD1	0.721				
DPD2	0.845				
DPD3	0.844				
DPD4	0.847				
DES1		0.773			
DES3		0.758			
DES4		0.834			
DES5		0.802			
WOR1			0.894		
WOR2			0.911		
WOR3			0.863		
PCS1				0.845	
PCS2				0.849	
PCS3				0.864	
CMP1					0.811
CMP2					0.780
CMP3					0.832

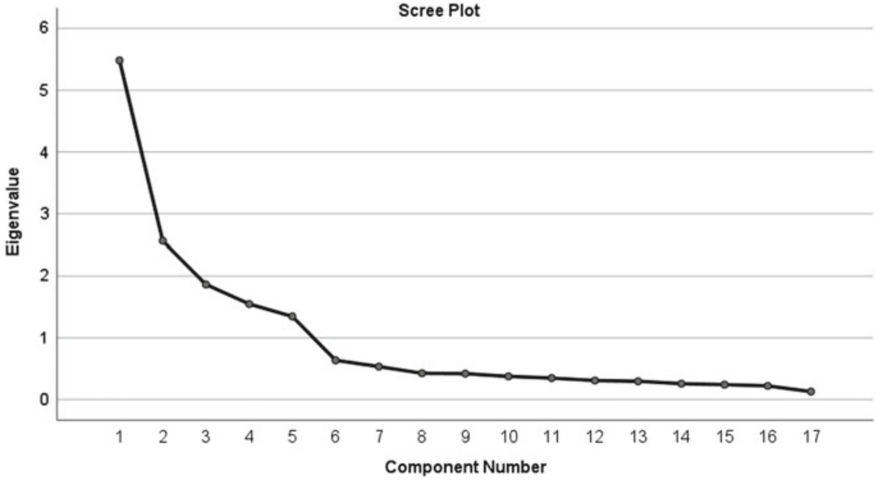

Fig. 1 Factor analysis—scree plot

Table 7 Total variance explained

Comp.	Initial eigenvalues			Rot. sums of squared loadings		
	Total	% of Var.	Cum. %	Total	% of Var.	Cum. %
1	5.481	32.244	32.244	2.901	17.067	17.067
2	2.563	15.077	47.321	2.666	15.684	32.750
3	1.864	10.967	58.288	2.594	15.257	48.007
4	1.548	9.108	67.396	2.504	14.732	62.738
5	1.347	7.922	75.318	2.139	12.580	75.318
6	0.636	3.741	79.059			
7	0.534	3.143	82.202			
8	0.426	2.507	84.709			
9	0.420	2.469	87.178			
10	0.376	2.211	89.389			
11	0.348	2.046	91.435			
12	0.309	1.818	93.253			
13	0.296	1.744	94.997			
14	0.257	1.514	96.511			
15	0.242	1.425	97.937			
16	0.221	1.302	99.239			
17	0.129	0.761	100.00			

5 Enablers: The Five Facets

We identified, verified, and validated the five facets (Fig. 2) for enabling the IoT regarding wearable medical devices. Relevant elucidations are provided in this part.

5.1 Dependability

Dependability, as an originally introduced enabler, is there as a vital element constituting availability, reliability, safety, and maintainability attributes. Unambiguously, these devices must satisfactorily ensure (1) readiness for correct service to let users use whenever they want to, (2) continuity of correct service to ensure reliable information, (3) absence of catastrophic consequences to letting users feel safe, and (4) ability for maintenance and repair to let users conveniently continue using. Table 8 shows the characteristics of the dependability enabler and relevant references.

Fig. 2 The enablers: the five facets

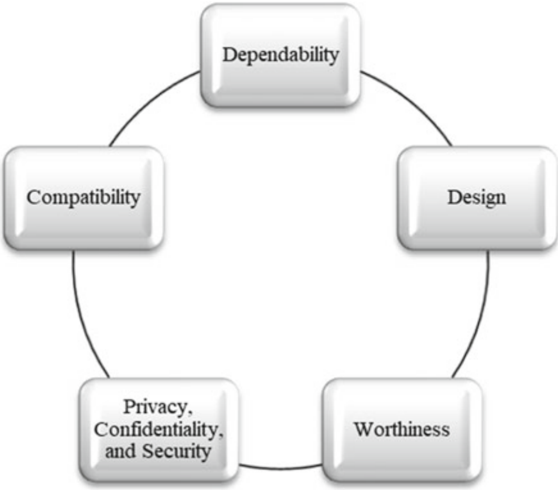

Table 8 Characteristics for the dependability enabler

ID	Enabler/Characteristics	References
DPD1	Wearable medical devices must ensure readiness for correct service to let users use them whenever they want to	[58, 65, 66, 86–89]
DPD2	Wearable medical devices must ensure continuity of correct service to let users have reliable information	
DPD3	Wearable medical devices must ensure absence of catastrophic consequences on the user(s) and the environment to let users feel safe	
DPD4	Wearable medical devices must ensure ability for maintenance and repair to let users conveniently continue using them	

5.2 Design

The design, as a modified and improved enabler, requires certain physiognomies. In this context, wearable medical devices must be lightweight and durable. The color and materials of wearable medical devices must be satisfying regarding aesthetics, convenience, and robustness. Moreover, comfort, interface convenience, and simplicity must be well-thought-out, and relevant and target users must be involved throughout the design. The exact details about the characteristics of the design enabler and pertinent references are given in Table 9.

Table 9 Characteristics of the design enabler

ID	Enabler/Characteristics	References
DES1	The color and materials of wearable medical devices must be satisfying regarding aesthetics, convenience, and robustness	[9, 13–15, 35, 69, 70, 89–102]
DES3	Relevant and target users must be involved throughout the design phases of wearable medical devices	
DES4	Wearable medical devices must be lightweight and durable	
DES5	Comfort, interface convenience, and simplicity must be considered during the design of wearable medical devices	

Table 10 Characteristics for the worthiness enabler

ID	Enabler/Characteristics	References
WOR1	Using wearable medical devices must offer value for money and effort spen	[9, 29, 63, 65, 67, 101, 103–110]
WOR2	The performance and quality value of wearable medical devices must be satisfactory	
WOR3	Purchasing and maintenance costs for wearable medical devices must be affordable for users	

5.3 Worthiness

Worthiness, as an originally introduced enabler, requires that using wearable medical devices must truly offer value for money and effort spent. Meanwhile, performance and quality must be satisfactory. Moreover, for this construct, purchasing and maintenance costs must be affordable. Table 10 presents the characteristics of the worthiness enabler and applicable references.

5.4 Privacy, Confidentiality, and Security

Privacy, confidentiality, and security, as a moderately standard and combined enabler, necessitate three foremost themes. First, relevant users must have the authority to determine what information to share, with whom, and how. Second, information must be used for the intended purpose only, and user consent must be taken first for any disclosure. Third, the protection to safeguard from unauthorized access to or modification, denial of service to unauthorized users, and provision of service to authorized users only must be ensured. Table 11 delivers the characteristics of the privacy, confidentiality, and security enabler and relevant references.

Table 11 Characteristics of the privacy, confidentiality, and security enabler

ID	Enabler/Characteristics	References
PCS1	Users must have the authority to determine what information to share, with whom, and how	[9, 29, 64, 67–69, 86, 89, 97, 100, 110, 115–119]
PCS2	Information must be used for the intended purpose only, and user consent must be taken first for any disclosure	
PCS3	The protection to safeguard from unauthorized access to or modification, denial of service to unauthorized users, and provision of service to authorized users only must be ensured	

Table 12 Characteristics for the compatibility enabler

ID	Enabler/Characteristics	References
CMP1	Using a wearable medical device must be consistent with my current preferences and habits	[13, 58, 64, 89, 97, 100, 111–115]
CMP2	Wearable medical devices must be compatible with my existing electronic devices (smartphone, tablets, computer, etc.)	
CMP3	Using wearable medical devices must be compatible with all aspects of my life	

5.5 Compatibility

Compatibility, as a modified and improved enabler, means using a wearable medical device must be consistent with people's current preferences and habits. Unambiguously, wearable medical devices must be compatible with people's existing electronic devices (smartphones, tablets, computers, etc.) and all other aspects of their lives. The particulars of the characteristics for the compatibility enabler and relevant references are provided in Table 12.

5.6 Checklist

Fundamentally, with extracted results, we crafted a novel and comprehensive checklist, given in Table 13, regarding the enablers for IoT regarding wearable medical devices to support healthy living.

Table 13 Checklist for enablers and relevant characteristics

Enablers	Relevant characteristics
Dependability	Ensures readiness for correct service to let users use them whenever they want to
	Ensures continuity of correct service to let users have reliable information
	Ensures absence of catastrophic consequences on users and the environment to let users feel safe
	Ensures ability for maintenance and repair to let users conveniently continue using
Design	Color and materials are satisfying regarding aesthetics, convenience, and robustness
	Relevant and target users were involved throughout the design phases
	Lightweight and durable
	Comfort, interface convenience, and simplicity were considered during the design of wearable medical devices
Worthiness	Offers value for money and effort spent
	Performance and quality value are satisfactory
	Purchasing and maintenance costs are affordable for users
Privacy, confidentiality, and security	Users have the authority to determine what information to share, with whom, and how
	Information is used for the intended purpose only, and user consent is taken first for any disclosure
	Protection to safeguard from unauthorized access to or modification, denial of service to unauthorized users, and provision of service to authorized users only are ensured
Compatibility	Using is consistent with the user's current preferences and habits
	Compatible with the user's existing electronic devices (smartphone, tablets, computer, etc.)
	Compatible with all aspects of the user's life

With the intention of determinedly attracting more people and improving user satisfaction, customer loyalty, and user experience, product developers and managers in the wearable medical devices business might take advantage of this checklist. Obviously, by using the checklist, given in Table 13, product developers can appraise maturities of their products and can identify main points to improve in order to boost their success.

For instance, regarding our distilled results, product developers are now able to know what the dependability is and what must be specifically addressed to ensure the dependability of wearable medical devices. That is, during design and development, for dependability, they need to confirm that their devices must satisfactorily ensure readiness for correct service to let users use whenever they want to, continuity of correct service to ensure reliable information, absence of catastrophic consequences to letting users feel safe, and the ability for maintenance and repair to let users conveniently continue using. Additionally, for example, product managers or marketers now be able to appreciate the importance of worthiness for wearable medical devices. Explicitly, for worthiness, they need to ensure that using wearable medical devices must truly offer value for money and effort spent. Namely performance and quality must be satisfactory, and purchasing and maintenance costs must be affordable for success. These are accurately valid for all of the distilled five enablers on account of distilled pertinent 17 items.

6 Discussion

With this research, we determinedly tried to answer further research calls by some other researches [105, 120–127]. As a fairly transdisciplinary exertion to some other related and noteworthy studies [36–38], this research lets us move quite rapidly forward in the related field. As wearable medical devices are becoming more popular and omnipresent not only for customers and users but also for developers and researchers [58–63], the results of our study are going to be valuable for all the stakeholders. Moreover, our results are similar to the results of [58], based on the fact that they also concluded that perceived risk and compatibility constructs along with the original technology acceptance model constructs are imperative for success. Besides, from the privacy perspective, just like [68], we concluded that privacy, confidentiality, and security of wearable medical devices are vital for success. Furthermore, similar to the perceived value factor in a noticeable study [67], we found moderately related enabler, worthiness, as a significant construct for the success of wearable medical devices.

Regarding enablers to enhance the success of wearable medical devices in the scope of our study, there are three main categories. The first category includes the enabler well-established and verified in the pertinent literature and applications, and it is the privacy, confidentiality, and security enabler. The second category includes the constructs that are to some extent modified and improved in the scope of our study, and these are compatibility and design. The third category includes the constructs originally introduced in the scope of our effort, and these are dependability and worthiness.

The applied fairly comprehensive methodology and results of this work are going to be helpful and guiding for other researchers in the related field. Additionally, the results of this research are going to be beneficial and supervisory for wearable medical devices product developers and product managers. Interested researchers and scholars in the pertinent study field may benefit from this research regarding study design and distilled results about the enablers and accompanying characteristics. Our results resolutely contribute to the success of wearable medical devices literature, and other researchers may benefit from the applied methodology and distilled results to expand and refine the pertinent body of knowledge. Specifically, for example, other researchers might reuse, tailor, or adapt the enablers in order to better understand and study critical success factors and enablers for IoT concerning wearable medical devices. Furthermore, product developers and managers in the wearable medical devices business might take advantage of extracted outcomes. Clearly, by using the distilled constructs and relevant items (elements, features, and/or situations) as a checklist or worksheet, given in Table 13, product developers can assess maturities of their products and can detect main points to improve in order to boost success. Specifically, thanks to our distilled results, interested parties now not only know the all-encompassing factors but also get the exact things to achieve related factors through relevant 17 items.

7 Conclusions

This chapter contributes to the relevant body of knowledge with five enablers through 17 items. The enablers distilled and verified are dependability; design; worthiness; privacy, confidentiality, and security; and compatibility. These contributions notably advance the pertinent understanding about enablers for IoT regarding wearable medical devices. Findings are going to be useful for researchers in the field to develop and refine the related body of knowledge, and for wearable medical devices product developers to attract more people and improve satisfaction, loyalty, and experience.

While this work is an authentic and prominent one in exploring enablers for IoT regarding wearable medical devices to support healthy living, there are a number of limitations and these can be addressed in future studies. To begin with, this work studied wearable medical devices in a general sense. Alternatively, it is also plausible to study on different categories of wearable medical devices one at a time. Clearly, for each category, i.e., smartwatches, smart clothes, smart glasses, sports/activity trackers, or various sensors placed on body, different studies may be conducted, and results may be compared and contrasted. Besides, future researches might be directed in a longitudinal way and with semi-structured interview portions to draw more comprehensive and loyal conclusions and implications.

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Introducing Gamification for Advancing Current Mental Healthcare and Treatment Practices

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1 Introduction

Investing resources into enhancing patients' health needs and their active engagement concerning their health is essential in advancing the quality of health care [15]. The rapid and far-reaching technological advances that this digital area has conjured, undeniably, provide a straight revelation about the future directions of assessment, diagnosis, and treatment of medical conditions. One such promising tool attempting to offer a futuristic expedition to the effective healthcare system is *gamification*. Despite being a relatively new concept that collaborates therapy and technology, gamification has garnered a considerable amount of interest from health experts to improve patients' engagement and compliance with the entire clinical and therapeutic process. There are various approaches in which gamification has been used to be operationally defined. Gamification, however, in its core essence, refers to introducing typical elements of game playing and digital game designs for non-game purposes [19].

As Deterding and colleagues [19] put forth, gamification amalgamates the following necessary components: *gamefulness*, which constitutes the behavioral quality of the games, *gameful* interaction, which is how the individuals interact with the game, and *gameful design*, which refers to the designing game elements for non-game settings. Since gamification exploits our engagement processes that further aid in enhancing health outcomes [42], the application of gamification in improving health behaviors has been sought to be exceedingly promising. Various efforts to ascent the adoption of gamification in different contexts of physical and

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_11

mental health—as diagnostic and treatment methods—are being presently implemented, particularly, using computer games and mobile phone apps. A few early studies on gamification suggest its possible benefits for psychological, cognitive, and behavioral changes or symptoms reductions in many mental disorders, such as mood disorders, schizophrenia, autism spectrum disorders, attention disorders, Alzheimer's disease, substance abuse disorders, and others.

The first three sections in this chapter provide technical and psychological foundations for the introduction of gamification in mental health care. Submerging different theoretical orientations, they document the interrelatedness of behavioral and cognitive theories in designing "serious games" and why gamification requires both the theories for its applications, and, finally, what are the domains where gamification has been shown to be effective. The subsequent paragraphs, therefore, firstly aim to provide a richer understanding of the existing applications of gamification in primary health care and mental health settings. Through an extensive literature review, this chapter indicates how a host of innovative technical methods (such as rewards) and games have helped advance the technique of gamification and its practicality in improving the objective assessment and treatment of various psychiatric conditions listed above. Provided the complexities and individual differences that exist in mental health issues, the following sections then delve into the challenges that may emerge when clubbing together these approaches in the assessment and treatment of mental health issues. However, as we shall see, the challenges can be carefully addressed if novel interdisciplinary approaches are utilized when designing gaming elements for mental health care.

In short, with an overview of an existing subset of literature that taps on the kinds of games being utilized for the purpose of gamification, this chapter aspires to illuminate its readers and mental health experts to identify opportunities, strengths, limitations, and future directions to make an informed decision about integrating gamification in the assessment, diagnosis, and treatment of mental health issues.

2 Gamification in the Primary Healthcare Sector

Gamification strategies are lately becoming ubiquitous in health-related contexts, with collaborative multidisciplinary efforts for various reasons. Some of the early gamification-based health applications were intended to encourage individuals to modify their maladaptive health habits (e.g., weight loss, eating habits, exercise, smoking, and hygiene). Similarly, through applying gaming principles, gamification has been objectively successful in its diagnostic uses and treatment purposes (e.g., adherence, long term care, and health literacy) [57].

As compared to other existing approaches to health care, gamification offers a plethora of advantages. For instance, games are sought to positively affect one's emotional responses, such as curiosity, optimism, and social competitiveness [44, 52]. Gamification also assists distressed individuals to bounce back from their negative emotional experiences and sometimes even help to replace their negative responses

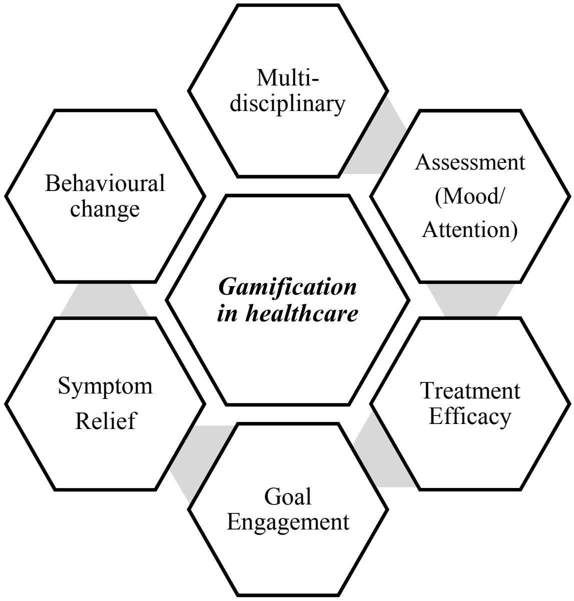

Fig. 1 Current description gamification in health care

with the healthier ones [45]. Likewise, cognitive faculties and psychomotor skills are also positively influenced when individuals are engaged in the complex environment of games [45, 51]. Other than these, these gamification strategies have been found to be equally effective for all age groups—from the children to the youth to the elderly [12, 30]. Since the healthcare contexts are vast and presenting an exhaustive list of all the gamified applications is beyond the goals of this chapter, some of the major healthcare domains where gamification strategies have been mentioned throughout the chapter. A few of the related fields where gamification is employed are—physical activity, diet, and weight loss programs, personal hygiene, and hygiene for healthcare workers, gamification for work environments, and health behavior/lifestyle changes. Figure 1 illustrates the possible advantages of gamification as complimentary to the conventional techniques available for improving healthcare domains.

3 From Primary Health Care to Mental Health Sectors

Computer games have emerged as a ubiquitous entertainment phenomenon among all age groups [13] worldwide. More than 40% of the US population invest their time in playing computer games, and 3/4th of all US residents have at least one gamer in their household in 2018 [22]. While the quality of computer games can distinctly differ from each other in terms of goals, interaction, and applied technologies, they have been shown to aid in enhancing and influencing multifarious cognitive dimensions, such as concentration [17], memory [2], learning [21], among others. In fact, some of the computerized games and apps are shown to facilitate health behavior [60]. Even though the trend of gamification is only a few decades old, it has, since its conception, seen various reforms over time in terms of its approach, quality, and goals. From basic line-dot games to augmented and virtual reality games, computerized games have been extended from its traditional objective of entertainment to educating, persuading, and motivating, as commonly catapulted by health, and education sectors [11].

Exhaustive research into the field of gamification in health care reveals that gamification has been primarily applied in physical fitness interventions and is mainly used in inculcating healthy behaviors among individuals suffering from chronic illnesses, such as short-term pain and arthritis [36, 66]. Although there exist various gamified versions of mental health interventions, they are relatively less common. This could be largely due to the fact that gamified apps work on the principle of providing monetary or emotional compensation (such as virtual money, coins, and bonus scores) and encouraging competitive behavior (such as multiple players) to enhance user engagement and motivation. Applying such strategies with games aimed for improving mental health could be somewhat inappropriate, for the reason that gaming elements may risk making distressed individuals even more distressed.

Unlike primary health care, gamification in mental health is still in its infancy. This is not to discredit the underlying point that there exist various benefits of gamification in the context of psychological and behavioral modifications—more specifically, in symptom relief [4, 24, 37]. At the moment toward understanding the implications of gamification in mental health, there has been an exponential growth in the smartphone applications for mental health [8, 50]. What makes these mobile apps a credible source for improving mental health and well-being is thus a relevant question. This means to enhance its reliability and validity for assessing, treating, and aiding in mental health improvements require extensive scientific testing in the future.

The forthcoming sections review the existing literature in length to inform readers about the current utility and applications of gamification in mental health. This is followed by real-world examples of gamification for readers and mental health users alike to explore the available resources.

4 Advancing Mental Health Diagnosis and Treatment Using Gamification

The population suffering from mental disorders (e.g., depression, anxiety, and psychosis) has drastically increased in counts. A report from the World Health Organization (WHO) indicates that mental illnesses affect one in four people, and as many as 450 million individuals are experiencing mental illness worldwide. These statistics are highly alarming, and that is why a need to facilitate mental health user engagement is highly imperative [56, 73] Mental health diagnosis and treatment methodologies have also witnessed profound changes in the way mental health is approached over the last decade. One such possible avenue where mental health has entered is gamification or "serious game playing." By applying some helpful insights from the behavioral economics models and the theoretical frameworks of clinical psychology, gamification in mental health diagnoses and treatments has shown some promising results and is becoming increasingly popular among experts and users. For example, various mental health games use an operational conditioning paradigm (e.g., rewards and punishments in terms of gaining and losing points) on how the users engage in those platforms (i.e., number of times they play). Since people have an inherent tendency for loss aversion (avoiding losses or unpleasant experiences) and often display endowment effects (i.e., irrational valuing things they own over the things they do not own), such taps usually tend to work in invoking necessary behavioral or cognitive changes.

Recent advancements in technology and its ease of accessibility in daily life have enabled researchers in the mental health community to utilize digital health tools in practice (Fig. 2). Findings from a line of studies done to test have shown tremendous effects of gamification on various mental disorders. For example, in their study on people with anxiety and depression, Andrew et al. [3] reported that individuals undergoing Web-based cognitive behavioral programs showed significant reductions in their anxiety and depressive symptoms. This is in line with Pinton et al. [58], who found that a game e-SMART-MH was instrumental in downplaying the effect of depressive symptoms. Other researchers also examined the use of apps like SPARX with adolescents with mild to moderate depression, and reported improvements in their symptoms [24, 53]. Likewise, Batterham and Calear [6] were also successful in replicating these results in their study among adults.

Furthermore, Lal and colleagues [43] also found that young patients with psychotic symptoms were more interested in using Web-based and mobile-based mental health services. The effectiveness of an early intervention using the Web-based modalities was also found in the context of eating disorders [32]. Studies

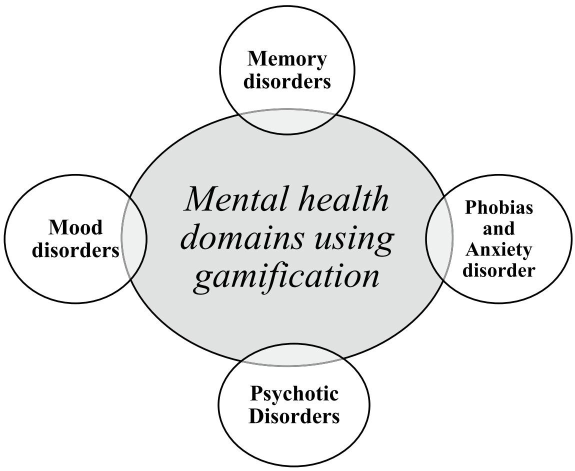

Fig. 2 Different types of mental disorders that use gamification as a supplement to the traditional treatment methods

that have assessed the effectiveness of interventions of sexual health promotion involving serious games have found favorable results in reducing a broad range of sex disorder-related symptoms [20].

The effects of serious games on youths have specifically shown tremendous possibilities in youth health management and treatment. Granic et al. [31], in their qualitative review published in the American Psychologist, asserted that there exists an honest potential of these intervention games in promoting well-being and reducing clinical symptoms, especially for youths since youths invest a vast majority of time in front of screens. As one of the primary factors that impede the entire process of psychotherapy or counseling involves high attrition rates among youths, and this can be critically reduced with naturalistically implemented Internet-based gamified interventions [7, 26]. Its ability to appeal, engage, and affect youths in making them become an active agent in their behavioral change with only little supervision from therapists or counselees, therefore, is truly remarkable [49, 59].

5 Psychological Theories Underlying Gamification

From behavioral theories (i.e., classic and operant conditioning) to expectancy theories (based on motivational processes), the psychological models and cognitive systems through which gamification seeks behavior modification are numerous. Therefore, only those theories that directly encompass the conceptualization of game elements in "mental health" applications are provided for the sake of brevity and specificity of this chapter (Fig. 3). This section is instrumental for readers to attain a meaningful insight into the upcoming section, which deals with the types of games presently available therapeutically.

(1) **Classical and operant conditioning theories**—Most of the traditional psychological interventions are based on the principle of rewarding positive behavior that patients display [74]. In a similar line, gamification in mental health to apply the same logistics through rewards and scores. Sometimes, users are also provided incentives for a small goal accomplished toward the change, which makes the principal tenant of operant conditioning.

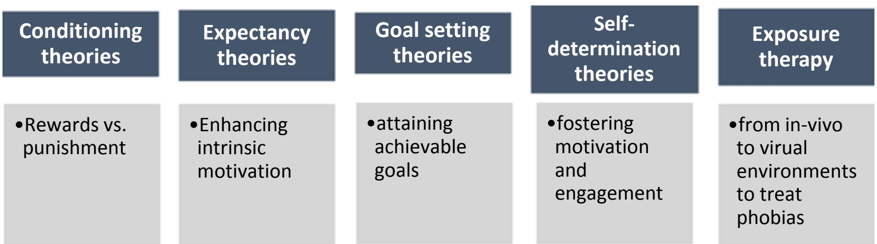

Fig. 3 Psychological theories underlying gamification in mental health

(2) **Expectancy theories**—Motivation plays a crucial role in instilling positive behavior or cognitive habits in individuals [71]. Many patients with mental disorders display a severe lack of intrinsic motivation; the role of the therapist, therefore, is to ensure that the patients are extrinsically motivated until they become intrinsically motivated with time [39]. Applied games, in forms of rewards and tokens, serve the purpose of keeping the users motivated to continue working on their behavioral goals.

(3) **Goal setting theories**—Gamification in mental health works on exploring ways to attain achievable goals [70]. Usually, it incorporates specific, measurable, attainable, realistic, and time-bound (SMART) goals to enhance the therapeutic process.

(4) **Self-determination theory (SDT)**—Factors such as autonomy, competence, and relatedness are contended to foster motivation and engagements of individuals [64]. STD, conclusively, proposes these psychological needs, if satisfied, can have a robust detrimental impact on the wellness of the individuals. Gamification in mental health thus attempts to capture these factors for the same rationale.

(5) **Exposure therapy**—Virtual reality/augmented reality (VR/AR) games mostly use the frameworks of exposure therapy to guide behavior change. Since individuals with phobia and anxiety issues may experience discomfort dealing with their issues in the real context, VR games utilize the concept of in vivo exposure to encourage participants to freely interact with the stimuli or events they fear using virtual environments [69].

While these aforementioned theories mainly decide the functionality and game elements of mental health games or gamified apps in general, there are many other theories, which also structure games that are designed to enhance well-being. In the upcoming section, the chapter will thus plunge even deeper into the existing categories of applied games for readers to acquaint them better with how gamification in mental health is actually conceptualized.

6 Existing Categories of Applied Games for the Therapeutic Change

Research in the field of gamification and mental health is relatively new and somewhat understudied. A systematic review, therefore, reveals a lack of rigid experimental approach to suggest its efficacy. For instance, there is no direct comparison between games and non-games interventions in various studies. While the robustness in these studies needs careful scrutiny, six primary types of applied gaming interventions can be identified based on its content, goals, and the potential mechanisms for behavior change and engagement [25].

6.1 Exergaming

Primary theoretical model: Behavioral activation, social activity

Active play gaming, also referred to as exergaming, is high-tech movement-based games, which approaches fitness and physical therapy using gamification techniques. Such games are centrally used in mental health for dealing with depressive symptoms, majorly among the elderly [47]. Since one of the key symptomatic factors that influence depression is the lack of interest or delayed motor activity, exergames allow patients to become more active. Another study by the authors [46] found a significant effect of playing exergames on depressive symptoms. However, these results need a better statistical interpretation, owing to a smaller sample size and the partial absence of randomized clinical trials in some of the studies.

6.2 VR/AR Gaming

Primary Theoretical model: Exposure therapy

Virtual reality (VR) and augmented reality (AR) gaming have been another potential way to introduce gamification in mental health treatment, as they offer two powerful tools of inducing engagement and motivation among users. These are presence and immersion [63]. Immersion in VR refers to a state of consciousness, wherein users feel as if they are physically present in that virtual world. This immersion is majorly achieved by using realistic sensory inputs, such as visual, auditory, and, sometimes, tactile. Presence, on the other hand, allows users to perceive as if the virtual environment they are presently navigating through can be easily manipulated and controlled as if it is real. Its immersive and interactive technology, therefore, significantly aids in enhancing patients' overall therapeutic experience by tapping on their perceptual and sensory elements. VR-based psychotherapy has mainly touched different domains of mental health, including anxiety, trauma, mood disorder, eating disorder, schizophrenia, and psychosis [16, 28]. For instance, in one of the VR exposure therapy, patients with fear of heights were allowed to interact and navigate through a virtual environment. Studies using these VR gaming interventions provide promising results, in terms of both its scientific effectiveness and commercialization [61].

6.3 CBT-Based Gamification

Primary Theoretical model: Cognitive behavior therapy (CBT), positive psychology intervention (PPI)

CBT, as a traditional psychotherapeutic intervention, has shown interesting favorable results in various mood disorders, such as depressive disorder or bipolar disorder even as computerized versions [29]. Research shows that the majority of the interventions that used CBT-based gamification was multi-level and often utilized a fantasy environment [53]. These games are designed in a way that they are needed to be completed at a rate of one level per week. Most of such games are targeted for children and youth. Some of these games have reported positive findings (e.g., SPARX, SuperBetter); others, however, have resulted in mixed findings (e.g., ReachOutCentral). These games are grounded on the theoretical modalities of CBT and PPI, wherein users have to progress weekly or biweekly in order to "level up." Some games also allow clients to achieve frequent, brief activity goals, which can be done a few minutes at a time, every day, or more frequently. In one of the recent gamification studies, participants were asked to play a gamified app for at least 10 min daily for a period of 30 days. It was found that these participants, as compared to the control group, experienced a significant reduction in their anxiety and depressive symptoms [62].

6.4 Biofeedback-Based Gamification

Primary Theoretical model: Psychoeducation, stress reduction therapy, biofeedback

Biofeedback-based games utilize the stress reduction models to encourage users to rehearse their relaxation skills and receive visual feedback on their physiological systems (such as heart rate and perspiration) simultaneously. Two of the most commonly used biofeedback games, as identified through the review of literature, are the Journey to the Wild Divine (include physiological monitoring and visual tasks, like building a bridge, or shooting a bow and arrow) and Freeze-Framear (includes heart monitoring). In their research on patients with depression and anxiety, Knox et al. [40] found that participants receiving such intervention showed significantly lower post-intervention levels of their symptoms. However, it should be noted that the sample size of the trail was too small. Such biofeedback games can especially serve a diagnostic utility in measuring the level of anxiety traits in individuals, and a similar line of research should be conducted to connect dots of diagnosis and games.

6.5 Cognitive Training-Based Gamification

Primary Theoretical model: Cognitive models of depression

Another way in which gamification has been applied to retrain the cognitive dysfunctions or cognitive errors use the cognitive models of depression, more precisely—cognitive training techniques. Not many games, however, have been scientifically tested, which use this modality. Alvarez and colleagues, in their number and letter sequence training games, reported a significant reduction in the cognitive impairments in the participants with depression. It is to be noted, however, that the direct effects of mood in this study were not assessed (as cited in Skorka-Brown et al. [68]).

6.6 Computer Gaming for Entertainment Purposes

Primary Theoretical model: Motivational theories, enhancing engagement and cognitive resources

While there is a serious dearth of games that directly translate to the mental health models (such as exposure therapy or CBT), entertainment-based computer games or applications are widely used in research to purport the effects of gamification in improving mental health behaviors. Such games are particularly used to assess the effects of video games on participants' mood states [47]. Mixed findings have been reported so far in this context, nonetheless. For instance, in a study by Ferguson and Rueda [27], the participants were first given a task that was meant to invoke frustration in them, and then they were either randomly assigned to play 45 min of a violent video game or to a control group condition. It was interestingly found that individuals who were in the experimental condition (i.e., those who were asked to play the game) reported a lower level of depressive symptoms, followed by an immediate intervention. In another study [72], however, no such effects on depression were found. Some studies found that there are several factors (e.g., emotion regulation, stress release, social pathways, etc.) that may mediate the effects of such entertainment games.

Even commercially, some apps and games are used for their therapeutic benefits, although they are not initially conceptualized for mental health purposes. Case in point, the puzzle game, Tetris—a game where players have to strategically move, rotate, and then drop the blocks in order to complete a horizontal line before the blocks spike up to the top of the screen. This game, which works on the engaging visuospatial function, has been proposed in inhibiting traumatic flashbacks in individuals with PTSD as well as in reducing cravings [34, 68].

Most of the e-health games are centered around improving moods and aiding in cognitive development. There exists a great amount of evidence that outlines the fact that gamification aids in the stimulation of brain processes as well as enhances knowledge acquisition (see Sardi et al. [66]), for a systematic review). Most e-mental health games are considered helpful for users to ensure full access to cognitive skills such as concentration, attention, problem-solving skills, and creativity.

6.7 Mood Assessment Apps

Primary Theoretical model: Depression theories, PPI, emotion theories

The mental health domain has seen a rapid scaling up of gamification in health management and treatment; and there still needs more exploration into multiple avenues of diagnosis and assessment. Mood tracking gamified applications, for example, can be classified under this category. Based on the traditional positive psychology theories, these games allow users to monitor or track their emotions and mood throughout the day and ultimately churn out statistics and trends to help users understand their mood better [23]. Specific tasks are assigned that users have to complete daily in order to earn points. These games have suggested clear success with users with depressive symptoms. The author's present research also attempts to adopt the technique of gamification in assessing depression vulnerability by collectively measuring the affective and attention systems of the individuals with and without depression. While all the games discussed above are mainly designed and utilized for therapeutic purposes and there is still a dire need to understand how such games can also facilitate the traditional and contemporary mental health assessment and diagnostic tools.

7 Current Opinions of Games in Psychotherapy

The acknowledgment of advantages of gamification in therapeutic experience comes from both the mental health service users and providers. Other than the individualistic goals of recovery, such game playing strategies also improve mental health by offering opportunities to gain social rewards. Considering that most of the contemporary mental health issues originally stem from feelings of loneliness and lack of interpersonal skills, gamification allows the users to not only regularly engage in a meaningful activity of some sort, but also to familiarize oneself with others on the same gamified platform [35]. For example, users who possess traits of introversion or are generally shy in personality can find ways to involve themselves in a shared environment. Unlike gamification in other domains, gamification in mental health is not necessarily competitive, where one is sought to pit against the other. In fact, there are apps that allow individuals to work together as a team. Moreover, since gamified counseling is not restricted to time and place, individuals can play "serious games" at their comfort. More functional elements, however, are needed to be incorporated to improve the functionality of these games. Say, for example, individuals getting extra points for doing exercise or cooking meals may boast their confidence to further their engagement with such applications.

In the context of the mental health service providers (e.g., clinicians such as psychologists, physicians, and psychiatrists), gamification in mental health has already conjured up various reforms in client-patient relationships. The change in the work culture brought about by gamification has altered the way conventional therapy has been recently approached, i.e., where the professionals earlier assumed the role of an advisor. With gamification, the role of mental health experts may become more of a coach, and the users have to assume a greater responsibility to bring any intended changes. Such reforms could be extremely influential in making remote rehabilitation an achievable goal (Fig. 4). Nonetheless, sometimes, users may feel extremely overwhelmed with taking an active agency in their underlying clinical conditions, especially among patients with serious mental disorders. For example, patients in their acute phase of disorder need a considerable amount of persuasion in their therapeutic journey from time to time. These patients may feel less motivated to continue with their gamified sessions and may need to be persuaded. Such apps,

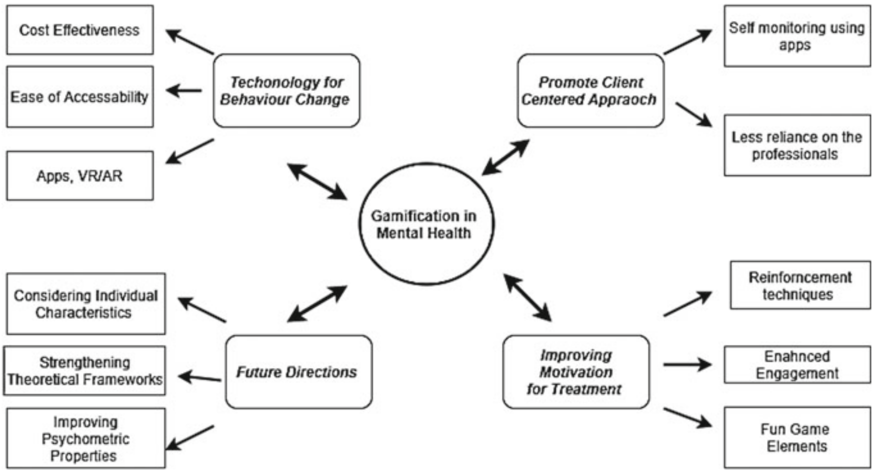

Fig. 4 Current description and future directions in gamification

therefore, must be designed in a manner that allows them to immediately connect with their specialist in case they feel the need to talk. Likewise, gamification using mental health apps makes it easier for the users to enter into a counseling-like setting in the comfort of their home since they no longer have to travel long distances for even short sessions with their experts [14]. While this flexibility may seem advantageous, it can be disputed on various grounds. For instance, patients with depression are often encouraged by their clinicians to go out more. Using gamified mental health apps, therefore, may lead to undesirable outcomes in such patients [35].

In summary, there are mixed opinions concerning gamification since mental health itself is an entirely complex and diverse domain. Despite reservations and acceptances, there is still a hopeful future for gamified apps or serious games in a world that is technologically connected [54]. The next sections, therefore, would further divulge into the potential limitations and future directions of how gamification can come into being.

8 Potential Limitations of Gamification in Mental Health Care

Despite the immense potential and popularity of applied gaming in mental health, this approach also suffers from its own share of limitations and criticisms. The primary limitation of gamification in mental health stems from its multidisciplinary approach to design gamification solutions. Building games require various disciplines to come together, including cognitive science, clinical psychology, software engineering, interface design, and usability. This multidisciplinary effort poses a serious challenge, as communicating the idea as a complex as the mental health requires extensive skill sets on the part of each collaborator. Even when there is a careful consideration of the behavior change theory in conceptualizing the gaming apps for mental health, implementing those games is certainly another mammoth task that require intensive deliberation.

Some other issues challenging gamification include costs, implementation speed, and users' preferences. The costs associated with developing a full-fledged game with high complexity and levels can often come in millions of dollars [5, 75]. Funding limitations may thus make it relatively challenging for researchers to venture into such scientific endeavors. Likewise, the speed of implementation of gamified apps is also critical, and assuming the time it takes to pilot, refine, test in RCT, and then publish such games may risk lagging them behind the newer methodological approaches at the time of the actual publication [26, 75].

As mentioned in the earlier section, the proponents of the self-determination theory suggest that humans are driven by their intrinsic motivation in an attempt to satisfy their psychological needs of autonomy, competence, and relatedness [64]. Gamification, in theory, also supports the theoretical framework of this theory, as empirical evidence strongly reveals that games indeed aid in increasing one's intrinsic motivation to change [65]. Mental health issues encompass an acknowledgment of a highly complex domain of well-being, however. And this approach of using positive reinforcement and extrinsic motivation, therefore, has often been criticized [10, 41]. Another criticism of gamification in mental health stems from a clear lack of explicit interconnectedness between the theory and application of gamification [33, 67]. While some game elements have been attempted to match the existing behavioral theories and techniques [1, 18], there still exist some errors in the theoretical translation of such games and apps [48].

Furthermore, while gamification may help induce motivation, behavior change requires more than merely invoking motivational factors [18, 38]. Michie and colleagues [55] proposed the behavior change wheel to suggest that capabilities and opportunities are significant contributors to behavior change. This is conceptually missing in present-day mental health and well-being games, which should be considered while designing such apps [48, 55].

9 Future Directions

While various theoretical approaches are considered when designing mental health games, gamification in improving mental health has largely focused on positive reinforcement models that have been widely criticized in the literature. An introspection into the existing studies in mental health gamification shows a clear lack of consideration of reasoning behind the mechanisms through which the researchers have tried to achieve gamification [33, 67]. Perhaps, the first step in improving the gamification culture in mental health would be to first strengthen and elucidate on to the theory behind the ways in which gamification is proposed to influence behavioral modifications.

In a similar line, the applications and implementation of gamification in mental healthcare contexts may be of immense futuristic vision. That means moving beyond simple touch games toward incorporating-aided technologies, such as proximity sensors, artificial intelligence, and geo-referencing. This first-hand communication of the potential mental service users through sensors and communication devices may advance the present diagnostic and treatment process of various mental disorders in an incredible way. For instance, gamified apps that use sensors may alarm individuals with obsessive-compulsive disorder (OCD) about the frequency and intensity of their obsessions and compulsions so that they can actively modify their maladaptive cognition and behavior themselves.

In a nutshell, to achieve the fundamental goal of designing psychotherapeutic interventions that empower and enable improvements in overall well-being of the population, it is essential to extend the single-construct focus of engagement as outlined in the literature [9, 36] to capture various psychometric issues when desigining and implementing gamification . The standardization of the applied games, like traditional mental health tools, will further allow the mental health users to view such a gamified version of well-being tools as something trustworthy. Applying the framework as outlined by the Collaboration of Maximizing the impact of E-therapy and Serious Gaming (COMETS), Fleming proposed four key ways to maximize the efficacy of gamified therapies in improving mental health [25]:

a. ***User-centered approaches***—Instead of utilizing one-for-all games, acknowledging that the preferences of users may vary tremendously is extremely required. Targeting the user's preferences, in contexts of their personal levels of engagement and motivation, therefore, may allow experts to address their mental health needs more carefully.
b. ***Extensive Collaborative efforts***—Collaborations with multiple sectors and research communities offer dual benefits. Firstly, the cost burden is significantly reduced if there are more sectors and jurisdictions involved. And, secondly, the skill sets and inputs from such collaboration allow researchers to develop more effective games.
c. ***Frequent testing and implementation***—Technologies and user expectations in technology-driven techniques tend to evolve at an exponential rate, which is why frequent testing is needed.

10 Conclusion

This chapter has illustrated the efficiency of gamification in the assessment and treatment of mental health and well-being. How blending the core principle used in gamification with the conventional psychotherapeutic interventions has been highly effective can be easily understood by its application in the assessment and symptoms relief of various psychiatric conditions. For instance, gamification can be used to teach individuals how to identify facial cues and body language through gamified tutorials to assess their mood or others. Likewise, game elements have also been used to help patients with memory and attention disorders to sharpen their attentional skills. While the preceding sections illuminated on important aspects of how and why gamification has received an undeniable enthusiasm from the mental health research community over time, making any further conclusive assumptions about its potential benefits in the patients' engagement and behavior change might be slightly premature. To begin with, assuming that gamification can replace traditional methods of therapy would be somewhat ambitious. Similarly, ignoring the individual differences when assigning any games to clients may also lead to adverse clinical outcomes in certain disorders, such as depression. The chapter also highlighted future directions and the limitations that presently cloud the diagnostic and treatment efficacy of gamified or serious games. Nonetheless, empirical evidence to support the effects of gamification in improving mental health domains strongly suggests that this field is a revolutionary one to plunge into. Moreover, the ease of accessibility, cost-effectiveness, and flexibility of games make it easier for mental health service users and providers to bridge the gap that usually exists between them. Given the increasing literature in this field, it can be, therefore, concluded that gamification is more likely to become mainstream and ubiquitous when it will come to influence mental health and allied health behavior. This chapter will thus be instrumental in helping mental health experts and clients in identifying possibilities of gamification in the assessment and treatment of such disorders. Future research should now focus on an interdisciplinary approach to improve the psychometric components (i.e., reliably and validity) as well as the user-centric components (i.e., engagement, appeal, and feasibility) of such gamified apps. Perhaps, combing traditional therapy methods with individualistically tailored gamification may emerge as a more pragmatic way to cater to mental health concerns in the near future.

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Impact of Digital Technologies on the Efficiency of Healthcare Delivery

Vladimir S. Osipov and Tatiana V. Skryl

1 Introduction

Informatization and automation of the healthcare sector worldwide, as well as in the Russian Federation, is a complex process consisting of many interdependent elements. Within its framework, several certain trends are monitored. Firstly, it is an active introduction of the Internet of Things products (IoT technologies) for various tasks. Secondly, it is an advanced analytics for the purpose of optimizing the activity of the clinic and the basic business processes of the enterprise (relevant for private medicine), and thirdly, it is an introduction of innovative expert systems for early diagnosis of diseases, as well as assistance to the expert.

Modern medicine has risen to previously unattainable levels in recent decades.

Today, the healthcare sector is a high-tech industry where transplantology and traumatology, plastic surgery and oncology, neurosurgery, ophthalmology, gynecology, dentistry, and other fields are successfully developed, which allow saving lives of previously hopeless patients.

Technical equipment of medical centers has been significantly improved, and it is now possible to diagnose the disease at the earliest stage and quickly restore the efficiency of patients. Minimally invasive procedures with the use of endoscopic equipment, microsurgery and laser correction of vision, transplantation of organs and tissues, correction of congenital and acquired defects have become usual.

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_12

Still, some problems are still existing, and to solve them, the Internet of Things (IoT) should be taken into account. IoT is one of the most popular innovative technologies in last years. The ability to implement practical solutions through the concept of the Internet of Things gives advantages in many areas of human activity.

Today, the development and introduction of Internet technologies is particularly important for the healthcare system. In this regard, experts are developing the conceptual apparatus and conditions for the practical application of the Internet of Things.

In the healthcare system during the pandemic, the technology of the Internet of Things has played an important role and assisted in monitoring the well-being of patients, tracking the location of infected patients and measuring temperature and pressure, as well as tracking indicators of the medical institution and its internal structure.

The purpose of this work is to conduct a comprehensive analysis and assessment of the main trends digital technologies' implementation in the healthcare system in two main areas—global (most innovative world achievements) and local (national trends) and assess the impact of digital technologies on the efficiency of healthcare delivery. In the course of the study, the authors consider the process of implementation of digital technologies in healthcare system on the example of international and domestic experience. In the context of modern processes of digital transformation, the healthcare system is being modernized in the main areas stimulating technological progress - the use of medical information systems (MIS), the introduction of Internet of Medical Things (IoMT) products, advanced analytics of large data (Big Data), and the practical application of expert medical systems. The results indicate that digital technologies make it possible to protect doctors and patients from forced contacts and avoid infection with dangerous infectious diseases. The traditional "patient–doctor" model is losing its relevance, and today's reality forces it to change significantly. Digital technology, together with medical devices, is ushering in a new era in digital health care, and the digitalization of the healthcare system itself is leading to improved delivery of health services, better quality control, and lower costs. The structure of the chapter is the following: to describe the methodology of the research, review the literature, discuss the results, and summarize the findings.

2 Methodology

The first point of our analysis will be medical information systems (MIS), which are the framework of the entire IT infrastructure of the enterprise. There are multiple interpretations of the definition of MIS. MIS can be defined as a set of software and hardware tools, databases, and knowledge designed to automate various processes running in the health clinics [1, 2]. This definition seems to be too narrow. Moreover, several crucial aspects of application are overlooked. Therefore, the authors consider other variant. MIS is a system of automation and document management for health clinics, which combines a system of support for medical decision making, electronic medical records of patients, research data in digital form, patient monitoring data from medical devices, means of communication between employees, financial and administrative information [3–5]. This definition is much closer to the practical implementation of the functions of a medical information system. However, it discloses too widely some of the details not required at this stage of abstraction.

In the opinion of the authors, the most appropriate definition of a MIS is a set of software and hardware tools, databases, and knowledge aimed at automating and digitizing document flow and providing the information needed to meet the needs of health clinic staff at all levels of its implementation. If we move away from the peculiarities of the implementation of specific systems, the architecture of MIS can be presented as in Fig. 1.

In most cases, the medical information system for the patient begins with the registration of the visit. Moreover, it can be done in many different ways such as by phone, through the Internet portal, by appointment of the previous visit. Already at this stage, MIS has a significant impact on the functioning of the company. With the help of call-tracking systems and analytics tools of the Internet portal, by the time of the call the operator is already informed about the identity of the patient (if he is a registered client), or is aware of his problem in general (with the help of ID numbers and logs we understand what advertising led him to us). Consequently, there is a process of referral and/or registration to a specific specialist, which is also noted in the system.

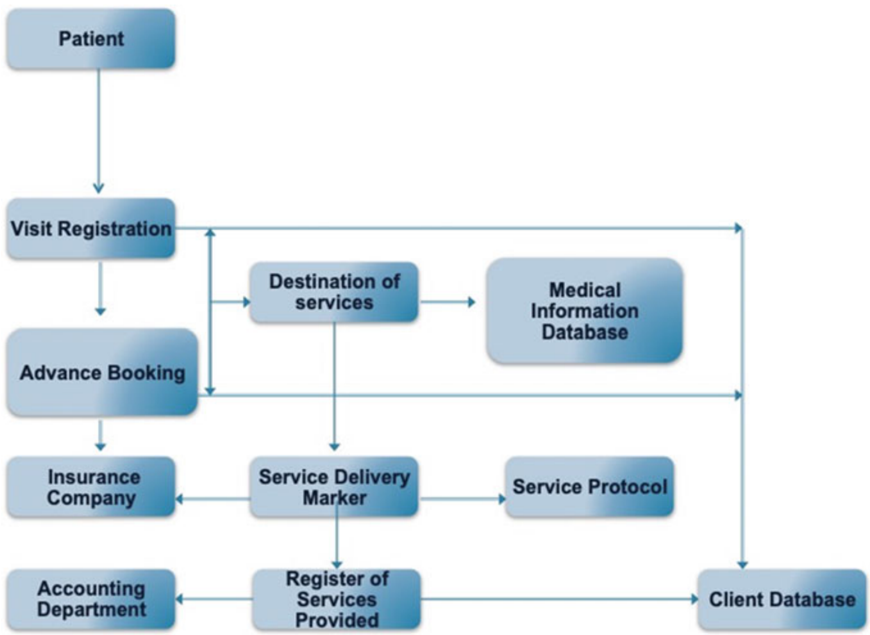

Fig. 1 Architecture of medical information systems

The application of MIS in Western countries started earlier than in Russia [6]. The foreign market has managed to form and mature, which means it has become more demonstrative for research. Therefore, the authors will review the main players and the platforms they use to build MIS. Based on the analysis carried out by Capterra [7], it is believed that the most popular MIS is designed for the Windows operating system and presents their software as a cloud solution. The third place by market share is occupied by the cross-platform EMR system, also partially functioning in the format of cloud subscription. Pure cloud solutions are also quite popular. However, these systems can be implemented only in small businesses, where the requirements for fault tolerance are much lower (e.g., no surgery). Currently, Microsoft Windows is the largest MIS development and operation platform, but at the same time, cloud solutions have a significant market share—17%, which is 4% more than MIS deployed on the basis of iOS [8, 9].

The MIS market in the Russian Federation is steadily growing, but to a large extent the activities of both developers and integrators, as well as users, are limited in regulatory terms. On the Russian market, the situation is quite similar to the global trends. The Microsoft is seriously ahead of its competitors by numerous indicators of prevalence [10]. Unfortunately, at present there are no relevant data on the implementation of cloud systems. However, almost of the leading Russian developers of MIS also offer a cloud version of the product, which means that this market has a share of consumers who prefer cloud technologies (partly or completely). Separately, it is worth mentioning the problems faced by developers of medical information systems in Russia. The main obstacle is a weak legal framework that does not keep pace with the pace of modernization in terms of technical progress. The activities of MIS fall under a multitude of regulatory and legal acts that have not been sufficiently developed to stimulate the further process of informatization. In particular, the federal laws 152-FZ "On Personal Data," 149-FZ "On Information, Information Technology and Information Protection," 323-FZ "On the basics of health protection of citizens in Russia," and Government Decree No. 1815-r "On the State Program of the Russian Federation Information Society (2011–2020)" [11, 12].

The results of the literary review showed that the problems of introducing digital technologies into medical management are not sufficiently developed and are very poorly covered, including in the following areas to the normative literature. The proposed methods are mainly aimed at the use of technical gadgets, or high-tech medical technology. In this regard, a new architecture of medical information systems and three-level system of decision making in health clinics are proposed. In two sources [13, 14] it is possible to find answers to questions of introduction of the Internet of Medical Things (IoMT). But in general, this question is not sufficiently developed: There is no economic substantiation, administrative characteristics, all conditions and possibilities of application are not designated.

3 Results

Before talking about the IoT and medical devices embedded in the overall information technology (IT) architecture, it is necessary to highlight the correct definition that most fully reflects the essence of the phenomenon under consideration. So, according to Gartner, the Internet of Things is a methodology of computational network of physical objects ("things"), equipped with built-in technologies for interaction with each other or with the external environment, considering the organization of such networks as a phenomenon capable of reconstructing economic and social processes, excluding the necessity of human participation from a part of actions and operations [15, 16]. IoT is the most used abbreviation, however, when we narrow down the discussion of phenomena to purely medical subjects, and the abbreviation IoMT—Internet of Medical Things—is also used.

In fact, all such subdivisions of the Internet of Medical Things are relative, but here we will try to consider their impact on the provision of medical services. In order to understand what these technologies can do for maximum benefit, it necessary to know what are the main weaknesses and vulnerabilities in the medical field that can be improved by using IoMT devices.

Firstly, it is the lack of qualified specialists. The modern hardware component with high-resolution webcams, equipped with a Wi-Fi module and a high-speed communication channel. In such conditions, specialists work in the USA state the lack of professionals in this field. As a response to this call, a special center for monitoring the condition of patients was created by a doctor on duty [1, 17]. The algorithm of actions is simple. The heaviest patients constantly wear a bracelet that reads the basic indicators of vital activity, and if the intensive care physician suspects certain violations, he calls the patient an ambulance (if he is at home) or communicates with the hospital stay, examines, and gives specific recommendations for care to staff. This is an established practice that has saved many lives [1].

As of the current period in the USA, approximately 30% of initial visits to a doctor are made using telemedical services [18]. This indicates the degree of their prevalence in general. Among those close in spirit, but slightly different in performance, we can name another device for tracking the health of elderly relatives living separately. The principle is the same. The main indicators are recorded online, and in case of deviation from the norm, an automatic call to the ambulance is made simultaneously with the notification of relatives. Another device for elderly people is a smart box of medicines, which controls their timely receipt with reminders [2].

Secondly, medical enterprises suffer from the problem of dirty hands. The possibility of error is genetically embedded in a person, so the most skillfully performed operation can be spoilt by not thoroughly washed hands [19]. To combat this disease, a special sensor was proposed, which reads and compares the amount of soap spent in certain types of rooms and the frequency of their visit by doctors or other involved medical personnel (with a chip in a badge or special card). As a result, the number of accidental hospital infections drops by a factor of several, and the managers monitor adherence to medical hygiene standards in general. Another critical problem solved by means of the Internet is the integration and communication of hospital equipment. The existing standardized medical communication protocol DICOM (Digital Imaging and Communications in Medicine) is far from perfect and is not supported by some equipment. The IoT can solve this problem by correctly linking all hardware components of health clinics [11, 19].

The Russian Federation is characterized by some lagging behind global trends in the field of healthcare informatization. However, the use of Internet devices for medical purposes is incorporated in Russia. Moreover, the introduction of expert medical systems and strategic plans for advanced Big Data analytics has been conducted. These experiments are local in nature, which is explained by the lack of flexibility in the economic and legal spectrum [2]. The same law governing the industrial Internet (and IoMT devices in particular) is being considered and prepared for adoption as early as mid-2016 [14]. Nevertheless, the interest from different levels of the vertical power cannot but gladden. It is a positive signal that makes it clear that the need to follow the current trends of digital transformation is being understood at the top. At the same time, there is a trend of growth of strategic initiatives, often duplicating each other. These initiatives have not had time to fully implement the concept of Unified State Information System (USIS), as well as an equally ambitious project Health Net, implemented by the Agency for Strategic Initiatives, which aims to connect most Russian citizens to the system of collection and analysis of data on health by 2035 [1]. This project directly assumes use of devices of the Internet of Things. However, it is not clear up to the end in what kind. The formulation itself is rather blurred. For data gathering, "bracelets, native gauges, contact lenses, implanted devices" will be used. It sounds very futuristic, but already in 2017, the first applied research on the development of implantable ECG monitors and drug dispensers is planned to be conducted [14].

In 2021, it is planned to introduce a single health passport for Russian citizens. According to a representative of a state agency, the Russian health care will expand the share of online medicine in the next five years [20].

However, a single health passport with the integrated electronic medical records is not yet implemented. This limits the experience of the Russian Federation in this area. There are specific examples of the introduction of Internet devices of things. Several hospitals in the capital use special bracelets for the most severe patients, in online mode transmitting information on the main indicators of vital activity. By 2021, it is planned to introduce special bracelets for quick access to the patient's history [21]. Moreover, in Langepas hospital (Khanty-Mansi Autonomous Okrug) bracelets with a special alarm button are used [22], and automatic appointment systems are introduced [19]. As an experiment in Moscow is tested by a medical expert system [23] which diagnoses lung diseases. However, the widespread use of such experiments in not funded nor the regulatory framework [24, 25].

After reviewing the most relevant components of which all medical information systems of the future will be (or are already being) built, it is necessary to determine the order and algorithm of their interaction. As for MISs, we proposed a thesis about the fundamental importance of such systems as a basis for further integration of IoMT devices, analytical systems, and medical expert systems. Taking into account

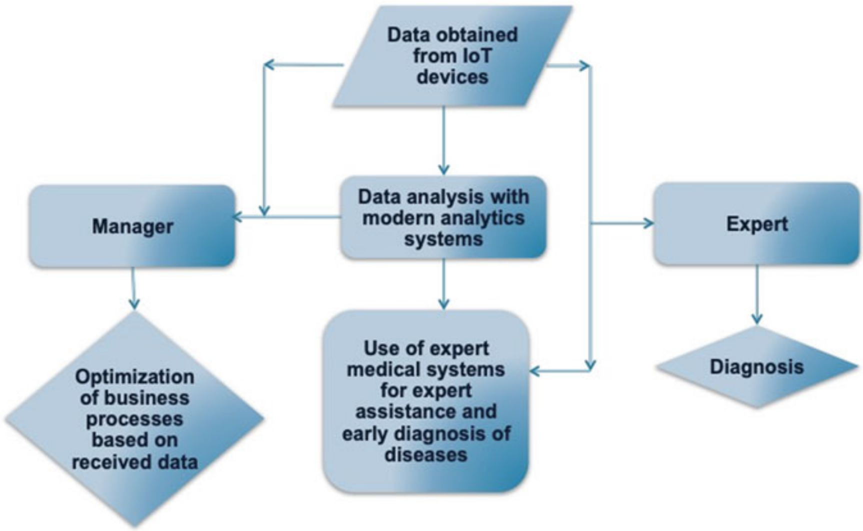

Fig. 2 Three-level system of decision making in health clinics

the already described functions of technologies of the digital transformation period, we can distinguish a three-level system of decision making in health clinics (Fig. 2).

As we can see from the scheme we offer, the hardware and analytical methods we describe may be relevant not only to physicians but also to managers. The scheme suggests a different approach to decision making, based on concrete, and most importantly, on proven facts [14]. There is always a share of probability that unexpected events will occur. But the minification of that is the main purpose of IoMT devices, analytical systems and medical expert systems, which open new horizons in the sphere of medical services provision [26, 27].

The current situation in the world shows that the traditional model of face-to-face healthcare delivery is changing significantly, and digital technologies will open up new opportunities in health care.

It is the medical sector as a whole that is becoming a driver of growth in digital and information technologies.

The market for digital innovations will grow thanks to the introduction of Internet technologies. These technologies make it possible to quickly and efficiently improve the quality of medical services, reduce the cost of treatment and consultation for patients, allow patients to seek advice from leading doctors, and have access to innovative treatment methods, especially in regions where high-tech medical facilities are not yet available.

The main problem to be solved when developing new medical technologies is the problem of processing the large volumes of data generated by IoT gadgets. Digital technologies, which are used today, allow scanning the entire human body instantly. Survey results in the form of images and signals are sent to a medical database and take up many gigabytes [19]. In other words, a medical facility must contain huge databases, which is economically inefficient. The size of the information received should be reduced.

The difficulty of processing large volumes of data can be solved by using digital tools that allow processing the incoming examination results and presenting them in the form of reports, graphs, and tables.

The use of digital tools for analytics of large databases would save the healthcare institution significant costs by reallocating the costs of innovative equipment, medical consultations, and prescription.

This is particularly relevant in terms of total health system financing by country. Table 1 presents countries that exceed the global average for health expenditure, and it is only top 15 of the total number of countries. Is that only 9% of the total number of countries. The top of this list for all three years is the USA. It is remarkable in this group of countries to single out Cuba. This country has maintained a high level of health expenditure over the years. If a correlation is drawn between health expenditures and the level and quality of health services provided, it can be concluded that the correlation is direct. The health systems of leading countries confirm this. Armenia and Afghanistan are in the leading countries in financing the healthcare system. These countries showed significant cost increases over the past year, which led to a rise in the list of countries. This fact will remain a topic for further research projects. The rest of the countries are far behind the world average trends.

Table 1 Current health expenditure (% of GDP), total 15 countries

	2015	2016	2017
World	**9.83**	**9.99**	**9.90**
United States	16.84	17.20	17.06
Switzerland	11.88	12.22	12.35
Afghanistan	10.11	10.96	11.78
Cuba	12.81	12.22	11.71
France	11.46	11.48	11.31
Germany	11.09	11.13	11.25
Sweden	11.00	10.98	11.02
Japan	10.89	10.83	10.94
Norway	10.11	10.52	10.45
Austria	10.37	10.42	10.40
Armenia	10.12	9.95	10.36
Belgium	10.28	10.30	10.34
Andorra	10.25	10.32	10.32
Denmark	10.23	10.18	10.11
Netherlands	10.32	10.30	10.10

Source www.worldbank.org, ranging by 2017

Table 2 Current health expenditure per capita (current US$)

Country rank	2010	2011	2012	2013	2014	2015	2016	2017
High income	4605	4953	4969	5041	5187	5025	5196	5369
Upper middle income	344	400	429	460	474	448	439	490
Middle income	198	228	243	260	266	253	249	274
Lower middle income	62	69	72	79	79	79	79	83
Low income	34	34	35	35	38	36	34	34

Source www.worldbank.org

Table 3 Current health expenditure (% of GDP)

Country rank	2010	2011	2012	2013	2014	2015	2016	2017
High income	11.57	11.60	11.73	11.86	12.02	12.43	12.62	12.53
Upper middle income	5.45	5.37	5.40	5.45	5.53	5.61	5.66	5.84
Middle income	5.07	5.01	5.07	5.16	5.19	5.24	5.27	5.39
Lower middle income	3.71	3.68	3.78	4.02	3.89	3.96	3.93	3.86
Low income	5.91	5.57	5.47	5.36	5.48	5.40	5.46	5.24

Source www.worldbank.org

Average global healthcare costs, as we can see from the Table 1, has decreased from 9.99 to 9.90. This decline was short-lived, and future data, especially for 2019–2020, will show us the increase in costs due to the spread of the pandemic. If we convert the data from the table for the enlarged groups, we can conclude that countries with high levels of health financing have higher living standards and quality of life, lower mortality rates and, most importantly, effective health service delivery (see Tables 2 and 3).

If we compare current health expenditure per capita (current US$) (Table 2) and current health expenditure (% of GDP) (Table 3) to each other, it can be seen that high-income countries have highest both indicators. Furthermore, the current health expenditure (% in GDP) (Table 3) shows that percentage of all countries besides high income are approximately at the same level. However, in current US$ (Table 2), this indicates as many times lower. We can conclude that gap in health expenditures in current US$ per capita much more than in % of GDP. This tendency can be explained by high-technologic medical care in high-income countries (especially in the USA and Western Europe).

The legislative framework for the development of telemedicine in most countries has not yet been adopted. However, in high-income countries this already happened in 2018 [2]. Technologies for using wearable electronics for remote monitoring of health have also not yet received widespread use around the world, while in the USA and Western Europe, this is already a daily occurrence [2, 11]. All these things will now be given serious acceleration if necessary measures are taken, including regarding emergency changes to the legislation. For example, in America, the FDA (Food and

Drug Administration) introduced an accelerated procedure for registering medical devices, primarily to accelerate the launch of coronavirus tests on the market [19]. In particular, the Abbott test, which allows testing for coronavirus in five minutes, was already approved by the accelerated procedure [11]. The widespread penetration of telecommunication technologies in recent years can be seen the complete transformation of the taxi market, the delivery of ready meals and products, goods, services, and payments. The same thing is happening with medicine. The traditional face-to-face reception will not disappear, but the current situation will accelerate the process of convergence of offline and online medicines, when the patient chooses an effective format in a particular case, convenient and affordable for himself. This format of medical care is already free to choose in high-income countries, but not spread widely in other countries. The unconditional effectiveness of timely obtaining information about the patient's condition using wearable equipment not only increases the efficiency of treatment, but also reduces the expenditures of more complex operations in advanced cases per capita.

The general trend of increasing funding for the global health system is still evident today. As we can see from Fig. 3, the USA remains the leader in health financing. It is the leader of high-income countries. These statistics indicate that these countries are at the forefront of medical developments and invest in the construction of MIS and implementation of IoMT devices.

Currently, healthcare facilities face the challenges, such as the safety of the staff, the need for continuous recruitment to improve performance, the ongoing monitoring of regulatory climate indicators, and the monitoring of patients' physical performance. The problems have a common reason which is the lack of a comprehensive solution that will continuously and continuously measure and monitor the processes,

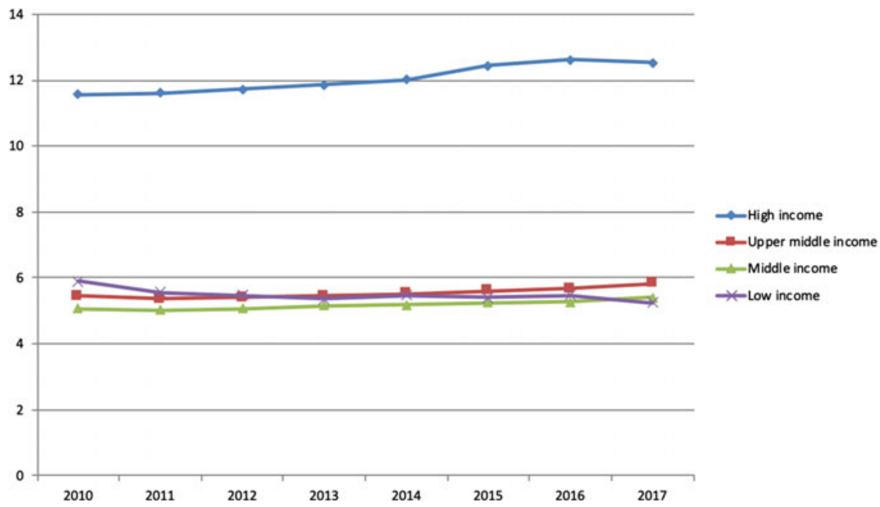

Fig. 3 Current health expenditure (% of GDP) by country rank

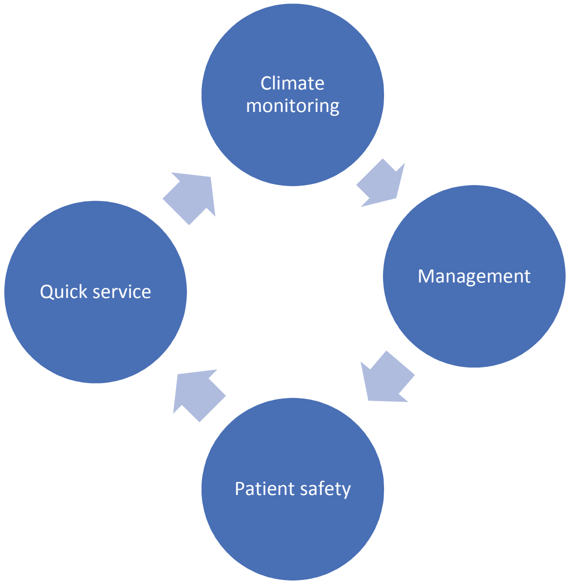

Fig. 4 Impact of modern technologies and automated monitoring on the patient's standard and quality of life

staff' behavior, quality of the service, environment, status and condition of patients, medical and other appointment.

These modern technologies and automated monitoring of environmental parameters will have a relevant impact on management, quick service, patient safety, and climate monitoring (Fig. 4).

Management: Real-time monitoring of the location of doctors and patients with the ability to call for emergency assistance in case of need and emergency (surgical operations or daily procedures such as hemodialysis), tracking the type, volume and condition of medical equipment, ensuring inventories and reporting.

Quick service: Automate equipment maintenance and repair process. A large video screen displays collected information about the condition of the medical facility. It is fully integrated with all equipment management systems, and reports are generated to improve the daily/periodic maintenance process.

Patient safety: Safety of the medical facility, staff and patients are the most important factor of reliability in patient care. Staff can use information about the patient's location and condition to ensure timely delivery of medical services, mobilizing waiting times. To help automate and maintain medical procedures, improve patient care and health, status information can be incorporated into current software systems.

Climate monitoring: The comprehensive solution will provide automatic monitoring of temperature, humidity, pressure, carbon dioxide concentration and other meteorological data, recording of events, collection of all necessary information in accordance with established requirements, displaying it on a single information screen, automatic notification in case of an emergency, ensuring the collection and archiving of data for any period of time and generating analytical reports.

The digital technologies in healthcare are a broad concept, and it can be interpreted in many ways. The "smart" bracelets, watches, and trackers transmit the maximum number of indications directly to the user's doctor. Moreover, the ideal to which everyone aspires is artificial intelligence that would analyze data about the patient and immediately give him recommendations on drugs and the necessary physical activity. However, today there are no such advanced gadgets, which could work online [28]. Furthermore, in the USA, UK and China doctors can remotely guide a patient, issue prescriptions, recommend treatment, and even prescribe electronic prescriptions [24, 25].

At present, telemedicine in Russia is underdeveloped. In 2019, the Russian market for telemedicine was about 2 billion rubles. Moreover, the world market is $45 billion. It is growing by 19.3% annually [7].

In several countries, doctors can perform diagnostics remotely. Several gadgets can be used for these purposes and can be divided into two types of services

- **Mobile applications and online services**. There are three groups: online clinics and aggregators, where you can find a doctor and get consultation, and specialized services for self-diagnostics;
- **Stand-alone devices**: Universal, for measuring individual indicators (glucometer), ultrasound and ECG. Typically, they also transmit data via a smartphone or laptop.

Moreover, telemedicine systems incorporate algorithms to remind patients of their medications, regularly interview them about their well-being and monitor the most important indicators. Using artificial intelligence, medical records are filled in, saving doctors up to 50% of their time. Artificial intelligence and data help to select a doctor and even make a diagnosis and to identify eye diseases or rare genetic diseases from a photograph.

Telemedicine as a publicly available medical practice is only just beginning to develop, although for a country with vast distances and underdeveloped transportation, telemedicine services are of particular social and economic importance.

Furthermore, telemedicine can be used for assistance in emergencies, assistance to military and astronauts, as well as for training and professional development of doctors.

Similar products are already available in Russia. For example, the service of remote medical consultations Yandex.Zdorovie in Russia, where the user can choose to consult a doctor at any time of day and chat with him. Or the telemedicine platform "Doctor at work" can be used by third-party companies to implement remote consultations with doctors [11].

There are two types of telemedicine: "doctor–doctor" and "doctor–patient." While the first one has long and actively been used in Russia, the second one faces serious challenges. In general, the patient can already now consult with a doctor remotely and send the results of tests after an initial in-person examination or consult with a famous specialist from another city on Skype [11].

The problem is that the legal status of such consultations is not fully defined. The patient cannot be sure that the doctor will be held responsible for the wrong advice and doctors cannot diagnose or prescribe treatment [11, 19].

4 Telemedicine Challenges

The first problem is the availability of modern technologies to the population. Not all Russia has gas and electricity, not to mention high-speed Internet and high-quality audio and video equipment. If you connect a polyclinic to a reliable Internet connection and reduce telemedicine to a conversation with a doctor from a local regional center or the capital, the question of efficiency will inevitably arise. Moreover is relevant to evaluate how will this doctor treat a patient if he is 100 km away. Moreover, it is also significant to check if this doctor simply would not duplicate a local paramedic, which is unnecessary at already modest medical expenses.

There is no certainty that older people can easily use the same software applications. Moreover, it is critical to evaluate the consequences if the connection is interrupted. On the one hand, these risks outweigh the possible benefits of telemedicine. On the other hand, the best solution will be found in the near future. Moreover, the patient may not always be able to buy the necessary equipment. Many modern devices for diabetics, people with chronic heart disease are not certified in the country, and local analogs do not always match the level of development or affordability.

There are many factors that do not allow for rapid development of telemedicine. Several limitations of the law on telemedicine, skepticism of patients and doctors, lack of IT infrastructure in clinics, lack of transparent and understandable standards for consultations. However, in large cities and regional centers, telemedicine can already save money both for patients and doctors.

The second problem is safety issues. It would be very convenient to create a full-fledged unified medical base all over the country with the possibility of access to it by any doctor. However, it is necessary to make sure that this base is well protected, and the data in it is securely encrypted.

Through a regular video call, a doctor can find out confidential information. Therefore, it necessary to ensure that it is used correctly and there are no cases when "black realtors" come to pensioners with mental disorders. Moreover, these are isolated risks, but they can become a serious problem if telemedicine is used everywhere.

The third challenge is doctors' willingness to work with telemedicine. Doctors have been reluctant to accept the computerization of polyclinics. Many specialists had a hard time learning how to use computers, which led to delays in patient care and deteriorating quality of appointments. A doctor cannot pay enough attention to a patient if half of an appointment requires entering passport data into a computer. Telemedicine technologies are more difficult to use, and the risks of making the wrong decision increase [8].

Consequently, it is not clear whether doctors will want to make a massive switch to IT when it comes to diagnosis and treatment, especially if it's not about advanced centers.

It should be noted that it is necessary to form a special center to conduct telemedical consultations with doctors. Furthermore, it is created in order to work out in real conditions the details of implementing information systems and telemedicine technologies in everyday medical practice. It is expected that the center will also play a role in training physicians to effectively use telemedicine.

The social consequences of the introduction of telemedicine for doctors are also important. Theoretically, it can lead to the reduction of the already small number of polyclinics in remote regions, which means that some doctors may find themselves unemployed [20].

It should be noted that conservatism in relation to telemedicine is typical for both doctors and patients. It may take a long time to ensure confidence in telemedicine technologies, and it will be necessary to thoroughly analyze the performance of medical providers and develop clear quality standards. The expert notes that the work on changing consumer patterns is always the most time consuming, and leaders will "rock the market" from scratch.

Fourthly, patients' trust in telemedicine is also a relevant challenge. People are used to classical medicine. Especially if we take into account that polyclinics are often visited by conservative people with distrust toward new technologies. Conservatism of the population at the first stages of telemedicine development is inevitable, as well as at the moment of mobile banking and other technologies, which change the usual way of life [10].

Patients' trust in telemedicine can be won by showing by a real example that there is value in online consultation, and it is real to get answers to health questions remotely. The more often people will receive quality care from high-class doctors, and the faster telemedicine will be a worthy alternative to searching for symptoms on the Internet.

The legalization of telemedicine without serious control over it can lead to the blossoming of alternative specialists. Moreover, telemedicine should not be perceived as incomplete medical consultations or "medicine for the poor" [16]. Otherwise, the queue for face-to-face receptions will only grow, because everyone will think that it is more reliable.

The fifth problem is legal regulation and the law on telemedicine. The absence of a law on telemedicine hinders the development of those medical centers that already wanted to work in the new format of telemedicine, but so far could only provide information recommendatory, rather than medical consultations [17].

It is expected that a Unified State Information System in health care will be created. For example, in Russia, the law 149-FZ "On Information, Information Technology and Information Protection" defines the operator of this system, the composition of the data processed in it, the legal basis for its functioning, and information interaction with other information systems. The law also defines the providers and users of data stored in the system.

The law allows for the provision of medical assistance and remote patient consultations using telemedicine technologies. It also authorizes the issuance of prescriptions for narcotic or psychotropic substances on paper or in electronic form using an enhanced qualified electronic signature of a doctor and the relevant medical facility.

5 Telemedicine Market

The development of telemedicine is worth pursuing in three areas such as the protection of patients' personal information, the availability of the Internet anywhere in the country, and the involvement of high-class doctors in consultations. According to our forecasts, it will take about 6–10 years to fully implement this approach to patient care. Communication with a doctor will be more therapeutic and consultative in nature [2, 11].

It should be noted that over the past few months, telemedicine has been undergoing a period of ultra-high attention, which has led to a rapid growth of various services to provide telemedical services. The market is overheated and will grow more slowly than many optimistic expectations that some players are likely to be upset and leave the market.

The market will gradually overcome the skepticism and mistrust of both patients and doctors. At the beginning of its journey, telemedicine will be carried out by commercial organizations and focused on a fairly narrow layer of early adopters of new technologies, but in a few years the market may mature to a larger-scale implementation of the world scale.

Particular attention is required to the role of artificial intelligence in telemedicine—first as a decision-making support mechanism and second as a number of services that directly help the patient. Artificial intelligence will be especially important in the construction of MIS.

While doctors in hospitals are busy with COVID-19 patients, the need for treatment has not disappeared, but has increased somewhere else. The fear of being infected when visiting clinics has led many to seek advice online. As the technical aspects of telemedicine develop, the range of diagnostic possibilities will increase. For example, already now in some clinics there are special devices with modules allowing the patient to measure the temperature himself, take high-resolution photographs to diagnose skin problems, to examine external hearing. Therapists have become the leaders in the number of remote medical consultations - 38% of clients use their services. The second place is occupied by pediatricians (24%), followed by urologists/gynecologists (9%), neurologists (7%), and ultrasound and CT consultations (6%). In response to the pandemic COVID-19, demand for psychotherapy services increased (16%). The data is based on the statistics of the clients of IC Sberbank Life Insurance, who use telemedicine as a free additional option (Fig. 5).

In March 2020, according to a study by Frost and Sullivan, the number of requests for video consultations increased by 50%, and individual providers of telemedicine reported that they received 15,000 requests per day more than before the pandemic.

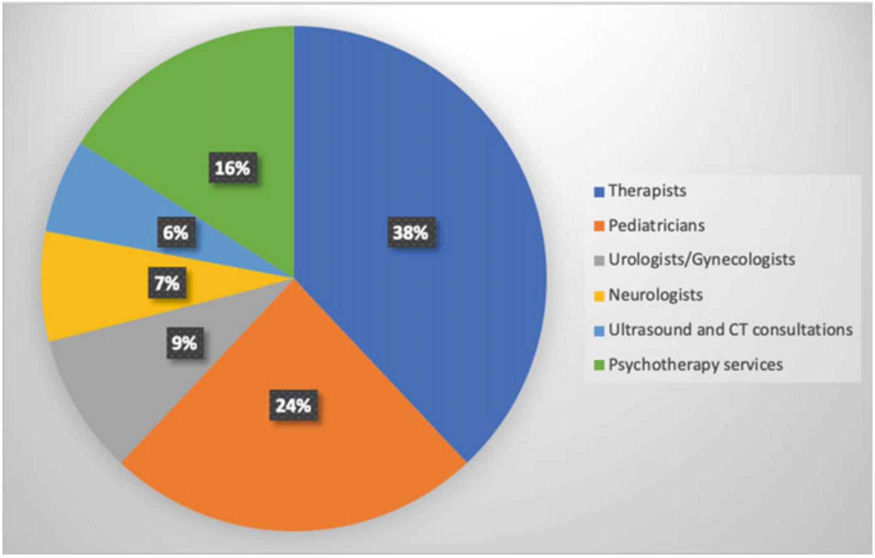

Fig. 5 Most popular doctors in telemedicine

Forrester analysts believe that this year due to coronavirus the number of requests for video consultations with a doctor in the USA may exceed 900 million [7, 27].

Video consultations with doctors are a way to help small private practitioners. In regions that are more heavily affected by the COVID-19, it is more appropriate to reduce the number of unnecessary face-to-face visits. That's why they are replaced by videoconference appointments. This is literally a lifeline for small private medical practitioners, as well as a lifeline for patients who would otherwise not have received help [22].

In Russia, a law on telemedicine has been in force since 2018 [11]. According to the document, doctors can consult patients remotely, but it is still prohibited to make a diagnosis and write prescriptions. A doctor is not allowed to make a diagnosis without a face-to-face examination. Consequently, he cannot prescribe treatment. However, it can correct it, if the patient has already been diagnosed, he began to treat, and something went wrong. It is possible to write electronic prescriptions. However, this has little to do with telemedicine: to get such a prescription, you or your relative must go to the doctor in person.

Furthermore, if there are no technologies in clinics, it does not mean that they cannot show up at your home. For example, the American company ButterFly Network sells the device with mobile ultrasound in 20 countries already [29]. It costs $2000, and another $50 will have to pay for a monthly subscription to a telemedicine application in iOS. Through the software, the doctor can get in touch with the patient directly and manage his actions.

In this chapter, the authors analyzed the main trends and successes in the development of informatization of health care around the world in general and in the

Russian Federation in particular. The main findings showed that digital technologies have a significant impact on medicine and the quality of medical services. The share of telemedicine is growing. Moreover, there is a widespread introduction of the Internet in medical institutions, there is a shift in demand for face-to-face visits to hospitals toward remote visits, and there is a lack of funding in the industry, which reduces the speed of creation and implementation of effective work of the medical institution. The presented three-level system of decision making in health clinics helps to improve the delivery of medical services and safe the costs.

6 Conclusion

The world technological progress provides medicine with the whole set of both hardware and software means which facilitate work of the doctor and the managing personnel of health clinics and at the same time reduce expenses for medical aid rendering. However, there are currently a number of obstacles that prevent the aforementioned tools from being put into operation everywhere. The most important are directly the lack of financial resources, as the lack of intellectual development of expert medical systems. Moreover, the threats associated with hacker attacks to IoMT devices store extremely important information, in most cases being in the process of providing the necessary information.

In most of countries at present, there is a clear lack of funding for state projects in the area of informatization of health care at the regional level, as well as duplication of some of the most important initiatives. The overall lagging behind the world leaders of the region is also characterized by an insufficient institutional and regulatory framework, which lags far behind technological progress. The proposed three-level system of decision making, based on the achievements of this period, will create a theoretical basis for a specific situation and minimize the risks of suboptimal outcomes.

The main limiting factor for research in telemedicine and the implementation of the Internet of Medical Things, and even more so in the digitalization of health care, is the uncertainty of public policy in this area. Several states around the world were seeking to improve the quality of health care while reducing non-productive costs in order to better manage health care. Benchmarking in this area allows the selection of global best practices for public policy development, which is a major factor of uncertainty and a limiting factor for research. The present study is based on best practices today, so their use in the development of public health policy is justified. The usage of the research results is goaled at increasing the effectiveness and quality of services in the health system. However, new experiences on a supranational scale, the development of new practices, may lead to the need to adjust public health policies, as digital technologies are changing very rapidly, and their implementation has mixed results.

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Digital Health or Internet of Things in Tele-Health: A Survey of Security Issues, Security Attacks, Sensors, Algorithms, Data Storage, Implementation Platforms, and Frameworks

Nadeesha D. Hettikankanamage and Malka N. Halgamuge

1 Introduction

Healthcare industry is undertaking digital technologies into the hospitals such as e-prescriptions, healthcare systems, statistical surveillance for detecting outbreaks diseases [1], ambulatory care, and clinical care [2]. Digital health in personal or industry has improved services for digital health applications (Remote patient monitoring, Tele-healthcare, and telemonitoring). The Internet of Medical Things (IoMT) can be known as IoT in healthcare [3]. IoMT is the collection of medical devices and applications that are connected to the healthcare systems. The practice of using IoMT devices to monitor patients can be known as technology-enabled care [4].

In digital health, many solutions have been introduced, and these solutions are becoming prominent between healthcare service providers, healthcare professionals, and patients. The healthcare solutions deliver benefits such as confidentiality of patients' data, low power consumption and long-distance communication, data integrity, data security real-time locating services, access control, handling a large amount of big data and improve the quality of life [5–10]. On the other hand, some technical challenges have been found, such as interoperability, security, and integrity [11]. Digital health provides convenience for people's lives, and contrariwise, it also creates new security issues. The highest risk of security threats were unauthorized access [12–18] and replay attacks. To secure the digital health system, network

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_13

and data storage, many studies have proposed different solutions, such as hybrid encryption schema [5, 19], privacy protector and data collection framework [6], ID-based cryptographic schema, user authentication schema as context-sensitive seamless identity provisioning [12], secure low power communication method (SeLPC) [7], obfuscation and return-oriented programming techniques which makes hard for the intruders to change codes and prevent reverse engineering [20], Open-Source Integrated Clinical Environment (OpenICE) incorporating with MQTT middleware, this provides a lightweight modularized architecture to integrate medical devices [21] and secure bootstrapping mechanism for IETF 6TiSCH protocol [22]. Along with these solutions, various algorithms have been used, such as encryption, cryptography, machine learning, LED, and multi-threaded processing algorithms [5–10, 12–16, 19, 23–30]. Furthermore, Rivest–Shamir–Adleman (RSA) and elliptic curve cryptography were the most used encryption and cryptography algorithms. Moreover, conventional technologies like, LAN, virtual private network (VPN) [28], and Global System for Mobile (GSM) module [30], LTE and LoRaWAN [7, 31] have been used to collect and transfer patients' medical data.

Additionally, recent advancements in digital health technology using sensors, wearable devices, as well as mobile devices [14] are used to gather patients' data. The collected data transfer via transmission media to the application is then data stored in various storages such as cloud, back-end servers, open-source databases, and grid infrastructure. With the arrival of digital health, the process of data collecting, transferring, and storing becomes more complex and insecure. Therefore, it is necessary to develop an efficient solution to ensure the confidentiality and integrity of patients' data [5].

This chapter provided an analysis of security issues, sensors and wearable devices, encryption and cryptographic algorithms, data storage, techniques, mechanisms, implementation platforms and frameworks that have been used to enhance the security in digital health. The data is collected from 30 experimental and peer-reviewed scientific publications. All of these articles were on enhancing security in the network, data storage, data communication, and health applications. The rest of the chapter organizes as follows: Sect. 2 provides the details of Materials and Methods, including how the data is collected and preprocessed. Results are presented in Sect. 3 with the analysis of security issues, security attacks, sensors, encryption and cryptographic algorithms, data storage, implementation platforms and frameworks. Section 4 provides a related discussion and, finally, the chapter concludes in Sect. 5.

2 Materials and Methods

A. *Collection of Raw Data*

This analysis is made through the experimental observation and peer-reviewed reported studies on the security in digital health. The raw data was collected from thirty (30) scientific publications. The materials locate from IEEE explore (Institute of Electrical and Electronics Engineers). Table 1 illustrates the data extraction of scientific publications.

B. *Data Inclusion Criteria*

To evaluate data inclusion criteria, data gathered from articles related to IoT-driven systems was extracted into a tabular format. We excluded publications which did not provide enough data for the data extraction table.

C. *Analysis of Raw Data*

The reviewed articles' data was classified into parameters such as healthcare applications, disease/medical condition/personnel, security issue, security attacks, encryption and cryptographic algorithms, data storage, sensors, programming languages, techniques/tools/mechanisms, implementation platforms and frameworks. Then, the analysis considered the relative frequency and percentage frequency of each instance.

D. *Statistical Analysis*

The raw data analysis result gained as frequency, relative frequency, and percentage values. Frequency is the number of times an instance (data) occurs. Relative frequency is calculated as frequency divided by a total number of instances, and the relative frequency value is taken into as percentage to illustrate the result.

Table 1 demonstrates the summary of raw data gathered from 30 peer-reviewed scientific publications.

E. *Digital Health Systems data*

3 Results

This research aims to analyze the security issues and solutions proposed by different publications. The raw data was collected from thirty (30) experimental and peer-reviewed scientific publications (Table 1).

Table 2 illustrates the security issues identified in digital health systems.

It is apparent from Table 2 that the unauthorized access was the most threatening issue, and this created most of the other security issues such as modify and inject messages into the network, change codes, and data leaking.

Table 1 Digital health systems

#	Study	Disease/medical condition/personnel	Application/network/subsystem/model	Security issues	Security attacks	Sensors	Data storage
1	Elhoseny et al. [5]	Early diagnosis	Patient's diagnostic data transmission model	Unauthorized access	–	Electromagnetic radiation	Cloud database
2	Luo et al. [6]	Early diagnosis	Storage system, data access control (PDAC) system	Data leakage Data breach	Collusion attacks	IoT sensor devices	Distributed database (multiple cloud servers) and back-end servers
3	Al-Turjman et al. [12]	Early diagnosis	E-healthcare application system	–	–	Heartbeat monitor Blood pressure Temperature Pulse rate Body movements PnP sensor (IEEE 1451.7)	Cloud storage
4	Eldosouky and Saad [32]	Emergency patients	m-Health IoT	Unauthorized access	Malicious attacks, remote attacks, brute force attacks, plaintext attacks, chosen plaintext attacks Cryptanalysis attacks	Medical sensors	Cloud
5	Tsai et al. [7]				Key attack, replay attack, eavesdropping attacks		
6	Bradley et al. [8]		Real-time locating systems (RTLS)	Unauthorized access Data leaks	Denial-of-service attack Data forging attacks		Cloud-based database, MySQL database

(continued)

Table 1 (continued)

#	Study	Disease/medical condition/personnel	Application/network/subsystem/model	Security issues	Security attacks	Sensors	Data storage
7	Almulhim et al. [26]		E-health applications		Impersonation attacks, man-in-the middle attack Unknown key sharing attacks		Server through base station
8	Arfaoui et al. [9]		Wireless body area networks (WBANs)	Authentication error unauthorized access	Collusion attacks, impersonation attack, replay attack, modification attack	Body temperature EEG ECG Glucose monitoring Motion Pulse oximetry, BS	
9	Varadharajan et al. [27]	Dementia patients in a hospital or elderly care environment		Congestion of the medium, unauthorized access	Flooding attacks, unauthorized SSID, broadcasts from rogue access points Traffic matching with the attack patterns	Real-time location tracking Wearable devices	MySQL database
10	Xin et al. [17]		Multi-feature fusion recognition system	Authentication error Unauthorized access		Image acquisition device (LED and CCD)	
11	Ivanov et al. [21]	Anesthesia, bronchopulmonary dysplasia (lung disease)	Remote pulmonary monitor system (RePulmo)	Communication error	Eavesdropping, replay, DoS	Anesthesia machine, Rad-8 pulse oximetry (oxygen saturation (SpO_2))	Relational database
12	Ullah et al. [33]	Elder personnel	Wireless body area network	Authentication error	Jamming Tempering Flooding	Temperature Heartbeat Blood pressure	Fog servers
13	Nausheen and Begum [20]	Chronic disease	mHealth application	Mishandled Unauthorized access		Wrist accelerometer	
14	Arfaoui, Letaifa et al. [34]		Wireless body area network (WBAN)	Authentication error, unauthorized access	Eavesdropping, Replay, Flooding, Sybil, DoS		

(continued)

Table 1 (continued)

#	Study	Disease/medical condition/personnel	Application/network/subsystem/model	Security issues	Security attacks	Sensors	Data storage
15	Aydin et al. [22]	Elder and vulnerable personnel	Home-based healthcare system	Authentication error			
16	Cagnazzo et al. [35]		m-Health application (HER/PHR)	Authentication error Unauthorized access		Gyroscopic, heart rate, bio-impedance	Cloud
17	Hamici [18]	Antibiotic resistance in bacteria	E-health-tele-monitoring system	Unauthorized access		Temperature, heart rate Pulse oximetry	Cloud
18	Binu et al. [36]	Sports personnel	Secure health monitoring for sports personnel, Android application	Interoperability of different devices Security of the system Streaming of huge amount of data	Replay attack Message manipulation attack, snooping Side-channel attack	Temperature Heartbeat/pulse Muscle Blood pressure sensors	Cloud storage (IBM Bluemix cloud environment)
19	Ray et al. [19]	Early diagnosis	Remote healthcare monitoring (RHM) system	Unauthorized access		Blood pressure Blood sugar Heart rate	Cloud database
20	Hao and Wang [23]	Elder personnel	SIoT (social Internet of things) healthcare system		Spoofing, impersonation Man-in-the-middle, exhaustive-search attacks	Electroencephalogram (EEG) Electrocardiogram (ECG) Blood pressure (BP) Motion sensors	Social network (SN) server
21	Naru [24]	Early diagnosis	Healthcare system, application of IoT	Unauthorized Misuses Data modification	Routing attack	EEG sensors ECG sensors	
22	Jaouhari [13]		E-health, internet-integrated sensing applications	Tampering		Accelerometer (ADXL335) Ultrasound (HC-SR04) Arduino UNO Blood pressure monitor	Web-based database

(continued)

Table 1 (continued)

#	Study	Disease/medical condition/personnel	Application/network/subsystem/model	Security issues	Security attacks	Sensors	Data storage
23	Pulkkis et al. [14]		Nursing home patient monitoring system	Modifying data		Blood pressure monitor Heart rate monitor Pacemaker Electronic wristbands Hearing aids	Server database, cloud storage
24	Mukherjee et al. [25]	Elder personnel	IoT-based application		Replay attacks	Heart monitor Beacon Geosensor	Edge of the cloud
25	Bari et al. [10]	Malaria vector borne disease	Smart health application	Illegal invasion Virtualization vulnerabilities Abuse of cloud services	Denial-of-service attacks Side-channel attacks	Sensing mobile devices Microphones Cameras Aerial Image Software logs	Quantum GIS cloud
26	Chiuchisan et al. [28]	Parkinson's disease	At-home health care systems	Unauthorized access	Intrusive attack		Open-source relational database management system (MariaDB), MySQL
27	Binu et al. [15]	Health and mind status of the children	Child health monitoring	Unauthorized access		Body temperature Blood pressure Heartbeat monitor	Local database
28	Nair et al. [16]	Bed rest patient	Healthcare system			Pulse rate sensor ECG	MySQL database, cloud
29	Aledhari et al. [29]	ICU, hospital rooms, rehabilitation units, or patients	Remote health monitoring system	Read, modify, and inject messages into the network	Key theft Man-in-the-middle attack Brute force attack	ECG, EMG, and accelerometers	Base station
30	Gabrani et al. [30]	Abnormal conditions and VIP patient	Patient health monitoring system			Heart rate Blood pressure Blood glucose Body temperature Respiratory rate	Grid infrastructure

(continued)

Table 1 (continued)

Programming language	Encryption and cryptographic algorithms	Technology	Techniques/merits/mechanism	Standards/legislation/principles	Methodologies/models	Implementation platform	Framework
Java Script	Hybrid (AES and RSA) embedding 2D-DWT-2L algorithm		Steganography (1-level and 2-level of DWT), watermarking		State-of-the-art methods, integer lifting wavelet transform (ILWT) method TSO (tree scan order)		Hybrid encryption scheme
XOR network coding	Secure hash algorithm 3 (SHA-3)		Slepian–Wolf-coding-based secret sharing (SW-SSS), Certificate authority (CA)		Secret sharing scheme Digital signature standard (DSS) scheme	Exclusive-OR (XOR)	Privacy Protector, a patients' privacy-protected data collection framework. patients' data access control (PDAC) ID-based Signcryption scheme ID-based Signcryption scheme
MIRACLE C/C ++	Secure hash algorithm (SHA) Elliptic-curve cryptography (ECC) Rivest–Shamir–Adleman algorithm (RSA)	Radio frequency identifications (RFIDs) Industrial internet of things (5G/IIoT)	Secure mutual authentication approach using hash and global assertion value personal data analyzer (PDA), data mining, inhabitant behavior in the detected context				Context-sensitive seamless identity provisioning (CSIP), user authentication scheme
DS-5 development studio	LED algorithm Symmetric algorithms (shared secret key)		Lightweight encryption techniques	ARM development studio (DS-5)		32-bit bit-sliced implementation	Hybrid encryption scheme (combining both symmetric and asymmetric encryption algorithms)

(continued)

Table 1 (continued)

Programming language	Encryption and cryptographic algorithms	Technology	Techniques/merits/mechanism	Standards/legislation/principles	Methodologies/models	Implementation platform	Framework
	Advanced encryption standard (AES)	4G, Wi-Fi Bluetooth Zigbee Ethernet				LoRaWAN environment	Secure low power communication (SeLPC) method
Python script	Encryption	Bluetooth Radio frequency identification (RFID) Wi-Fi	Hydra		Cracking tool hydra to gain access to the MySQL cloud database	Raspberry Pi 3 Model B, with built-in Wi-Fi running the Raspbian OS, a wireless USB dongle, and a power shim connected to a 12000 mAh lithium battery for portability	
	Elliptic curve cryptography (ECC)			ECC principles	Group-based authentication model		Group-based authentication model
	Signcryption, designcryption		Cipher-text policy attribute-based Signcryption (CP-ABSC) and identity-based broadcast Signcryption (IBBSC)				(Context-aware authentication and access control approach) Hybrid Certificate less Signcryption (H-CLSC) scheme
Linux kernel (2.6)	K-nearest neighbor algorithm)	Real-time location tracking	SDN-based techniques (global network knowledge and per flow decision making) Data mining			ONO SSDN controller and open flow access points, blueprints graph API	SDN separation of the control plane from the data plane

(continued)

Table 1 (continued)

Programming language	Encryption and cryptographic algorithms	Technology	Techniques/merits/mechanism	Standards/legislation/principles	Methodologies/models	Implementation platform	Framework
	Machine learning algorithms		Data mining		Linear gray-scale adjustment normalization method Niblack method Knowledge-based statistical learning method Gaussian mixture model (GMM)		Multi modal biometric recognition based on face, fingerprint, finger vein
	Encryption (symmetric and asymmetric)	LTE 4G				CHOP	OpenICE-Lite (open-source integrated clinical environment)
C#	Adaptive chunking algorithm (ACA) Encryption	3G, LTE, Wi-Fi	Lightweight de-duplication mechanism				Secure De-duplicated Data Dissemination (S-DDD) scheme
	White box encryption		Access control mechanism to prevent reverse engineering, Straight forward tamper-proofing technique, IMD access patterns	Food and drug administration (FDA) US			Obfuscation and return-oriented programming
		WBAN	Markov decision process (MDP)				Stochastic game is to balance the tradeoff between network performance and security level
	Encryption	LAN				Contiki OS and Cooja emulator for TIexp5438 embedded platform	Secure Bootstrapping mechanism (IETF 6TiSCH protocol)

(continued)

Table 1 (continued)

Programming language	Encryption and cryptographic algorithms	Technology	Techniques/merits/mechanism	Standards/legislation/principles	Methodologies/models	Implementation platform	Framework
	Encryption	WLAN, Bluetooth		Digital imaging and communication in medicine (DICOM)	STRIDE method		
	Cryptography	Wi-Fi					Genetic algorithm for data security
Java socket	Multi-threaded processing algorithm		Rule engine, decision making, Big data, machine learning, data regression or classification, cryptographic puzzle mechanism	Elliptic curve Q-Vanstone (ECQV)		Arduino MKRZero board	
eXtended Access Control Markup language (XACML)		Bluetooth	Data-centric approach	Health insurance portability and accountability act (HIPAA), NIST Next-Generation Access Control (NGAC) framework	Attribute-based access control (ABAC)		Healthcare plane (H-Plane)
	Elliptic curve point Keyed-hash message authentication code		Encrypted using a session key		Carrier frequency offset (CFO) IQ imbalance (IQI)	Social networks (online platform)	Device-specific physical-layer (PHY)
JAVA micro-edition software development kit	Lightweight cryptography algorithms and classical cryptographic algorithm		Notarization security mechanism HEDUN			Hardware and software	
Java Script	End-to-end encryption	WebRTC, WoT, CoAP-DTLS		IETF and W3C, 6LoWPAN standards	(CoAP) messages using DTLS, node-mbed-dtls module	Node.js	WebRTC and WoT
	Cryptographic algorithms (RSA, ECC, SHA with sufficient key length)	Tamper resilience of blockchain, wearable technology	Data mining	General data protection regulation (GDPR)	Hardware reliability prediction methodology		

(continued)

Table 1 (continued)

Programming language	Encryption and cryptographic algorithms	Technology	Techniques/merits/mechanism	Standards/legislation/principles	Methodologies/models	Implementation platform	Framework
C/C ++, using GCC compiler	RSA (Rivest–Shamir–Adleman), DH (Diffie-Hellman)	iBeacon				GENI Cloud-cloud-fog communication	End-to-end IoT security middleware for cloud-fog communication
Unified modeling language	Symmetric keys		Quantum GIS, discretionary access control Mandatory access control	Principle of CIA	Spiral model of object-oriented software engineering (OOSE) method	Cloud-based computing environments	SoA-Fog (Service-Oriented Architecture): three-tier secure framework
The Hypertext Markup Language (HTML), Hypertext Preprocessor (PHP), C#	Encryption	Virtual private networks (VPN) Web technologies				Virtual private network (VPN)	
	C4.5 decision algorithm	(LTE/3G/Wi-Fi) Android therapeutic games	Data mining, Sqoop			Hadoop	Apache Ranger instead of BISE [Big Data Service Engine]
PHP 1 (Hypertext preprocessor)	Advanced encryption standard (AES)	Raspberry Pi	Php MyAdmin tool			Raspberry Pi	
Python 2.7	Cryptography		DNA-based encryption Chaotic logistic maps			SHIMMER platform	Hybrid real-time cryptography algorithm
Object-oriented programming languages	Rivest–Shamir–Adleman (RSA)	Global System for Mobile (GSM) module				Wireless sensor networks and grid computing paradigm	

Table 2 Security Issues

#	Study	Digital health systems/network/subsystem	Security issues
1	Elhoseny et al. [5]	Patient's diagnostic data transmission model	Unauthorized access
2	Luo et al. [6]	Storage system, data access control (PDAC) system	Data leakage Eavesdropping Impersonation Data integrity Data breaches
3	Al-Turjman et al. [12]	E-Healthcare application system	–
4	Eldosouky et al. [32]	m-Health IoT	Unauthorized access the patients' critical data
5	Tsai et al. [7]		Eavesdropping
6	Almulhim and Zaman [26]	E-health applications	–
7	Arfaoui et al. [9]	Wireless body area networks (WBANs)	Authentication error Authorization access
8	Bradley et al. [8]	Real-time locating systems (RTLS)	Unauthorized access Data leaks Data forging attacks
9	Varadharajan et al. [27]	–	Congestion of the medium Unauthorized access
10	Xin et al. [17]	Multi-feature fusion recognition system	Authentication unauthorized access
11	Ivanov et al. [21]	Remote pulmonary monitor system (RePulmo)	Communication error
12	Ullah et al. [33]	Wireless body area network	Authentication error
13	Nausheen and Begum [20]	mHealth application	Mishandled Unauthorized access
14	Arfaoui et al. [34]	Wireless body area network (WBAN)	Authentication error Unauthorized access
15	Aydin et al. [22]	Home-based healthcare system	Authentication error
16	Cagnazzo et al. [35]	mHealth application (HER/PHR)	Authentication error Unauthorized access
17	Hamici [18]	E-health tele-monitoring system	Unauthorized access
18	Chiuchisan et al. [28]	At-home health care systems	Unauthorized access to a hard disk Unauthorized access to the application

(continued)

Table 2 (continued)

#	Study	Digital health systems/network/subsystem	Security issues
19	Binu et al. [36]	Secure health monitoring for sports personnel	Interoperability of different devices Streaming of huge amount of data
20	Ray et al. [19]	Remote healthcare monitoring (RHM)	Unauthorized access
21	Hao et al. [23]	SIoT (social Internet of things) healthcare system	–
22	Naru [24]	Healthcare system	Unauthorized, misuses, data modification physical security of devices
23	Jaouhari [13]	E-health Internet-integrated sensing applications	Eavesdropping and tampering
24	Pulkkis [14]	Nursing home patient monitoring system	Modifying data Changing the code of the device Eavesdrop the network
25	Mukherjee et al. [25]	IoT-based application	–
26	Barik et al. [10]	Smart health applications	Network eavesdropping Illegal invasion Virtualization vulnerabilities, abuse of cloud services
27	Binu et al. [15]	Child health monitoring	Unauthorized users
28	Nair and Kiran [16]	Healthcare system	–
29	Aledhari et al. [29]	Remote health monitoring system	Read, modify, and inject messages into the network
30	Gabrani and Gupta [30]	Patient health monitoring system	–

A. *Overview of Security Issues in Digital Health*

Figure 1 demonstrates an overview of security issues. The highest rate of security issue reported was unauthorized access at 61.11%, and another high-security issue reported was authentication error, at 16.67%.

B. *Various Security Attacks in Digital Health*

Figure 2 demonstrates an overview of the security attacks by percentage. According to the result generated from the analysis, the highest percentage of widely used attack was replay attacks (13.33%). Another high-security attack reported was denial-of-service (DoS) attacks (8.89%).

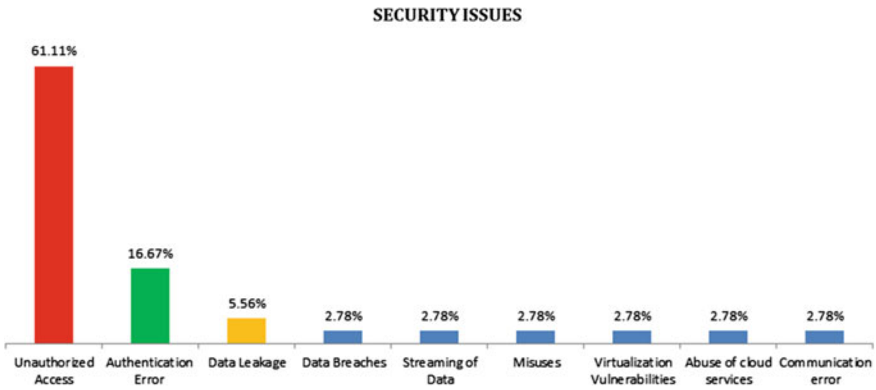

Fig. 1 Overview of security issues

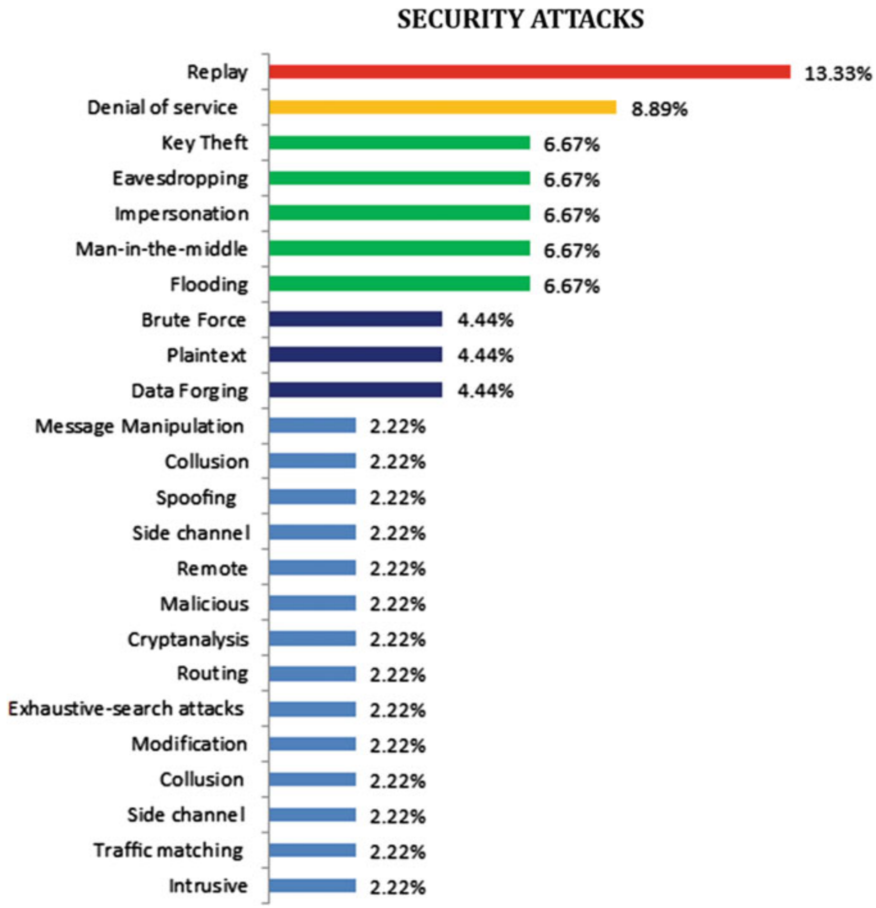

Fig. 2 Overview of various security attacks

C. ***Overview of Encryption and Cryptographic Algorithms used in Digital Health Systems***

Figure 3 demonstrates an overview of the encryption and cryptographic algorithms. The highest rate of algorithm reported related to encryption (65.71%), and another high algorithm reported related to cryptography (20%).

D. ***Comparative Analysis of Encryption and Cryptographic Algorithms***

Figure 4 illustrates an overview of encryption and cryptographic algorithms which were used most in (Fig. 3). It can be seen that the Rivest–Shamir–Adleman (RSA) from encryption algorithm and elliptic curve cryptography (ECC) from cryptography were the most used algorithms, and proportions were 38% and 28%, respectively.

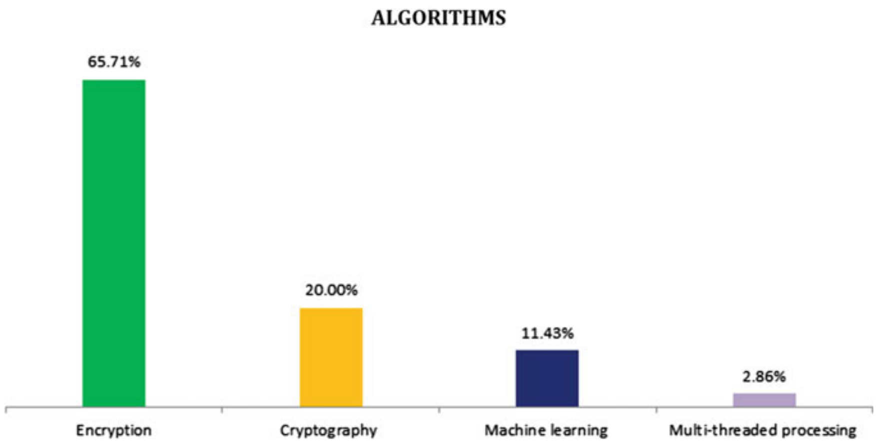

Fig. 3 Overview of encryption and cryptographic algorithms used in digital health

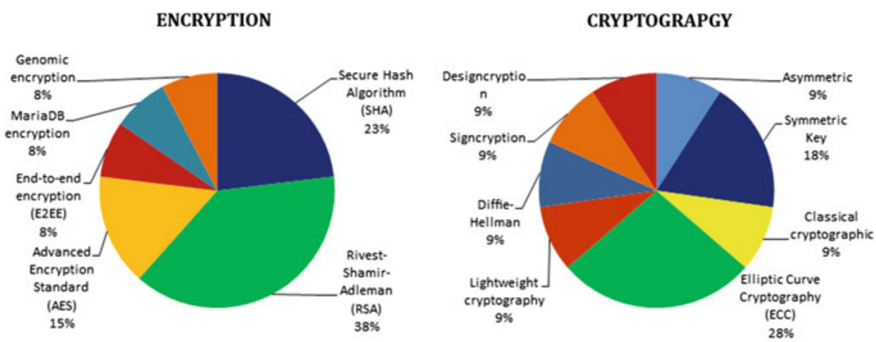

Fig. 4 Extraction of encryption and cryptographic algorithms

E. ***Overview of Sensors/Wearable devices used in Digital Health Systems***

Figure 5 demonstrates an overview of the sensors. The highest percentage reported from electrocardiography (ECG) (23.19%). The second highest percentage reported blood pressure monitor (11.59%).

F. ***Overview of Transmission Media***

Figure 6 demonstrates an overview of the transmission. The highest proportion reported was in Wi-Fi technology (34.29%) and the second highest reported was radio frequency identifications (RFIDs) at 25.71%.

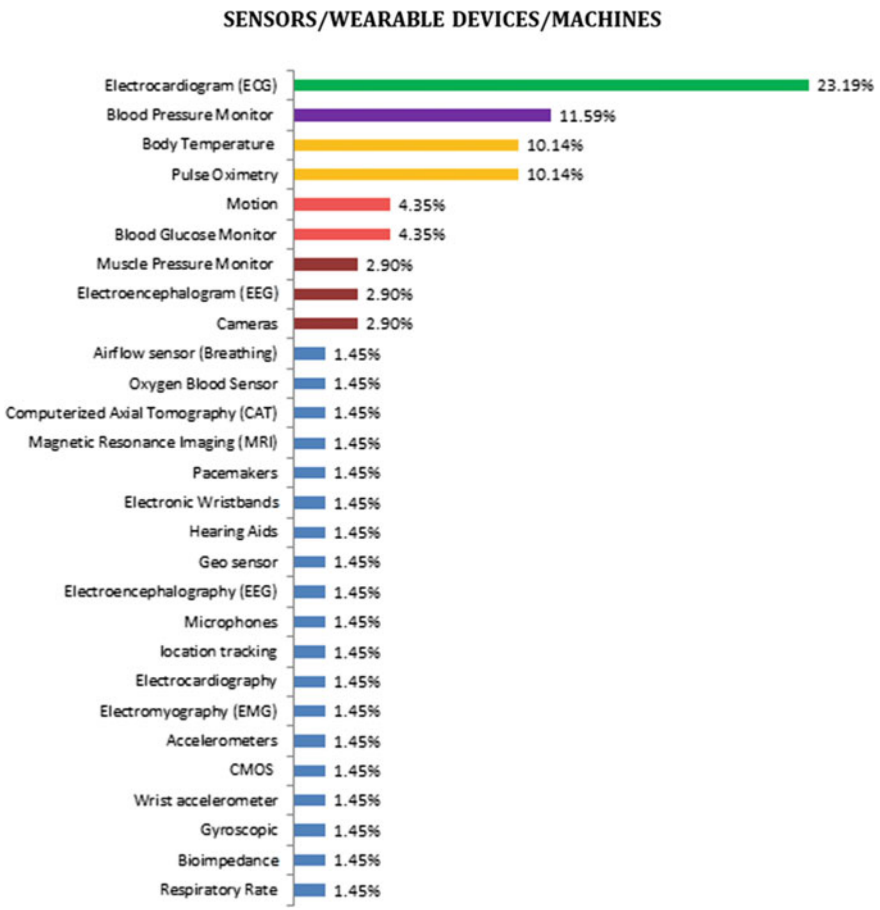

Fig. 5 Overview of sensors wearable devices used in digital health systems

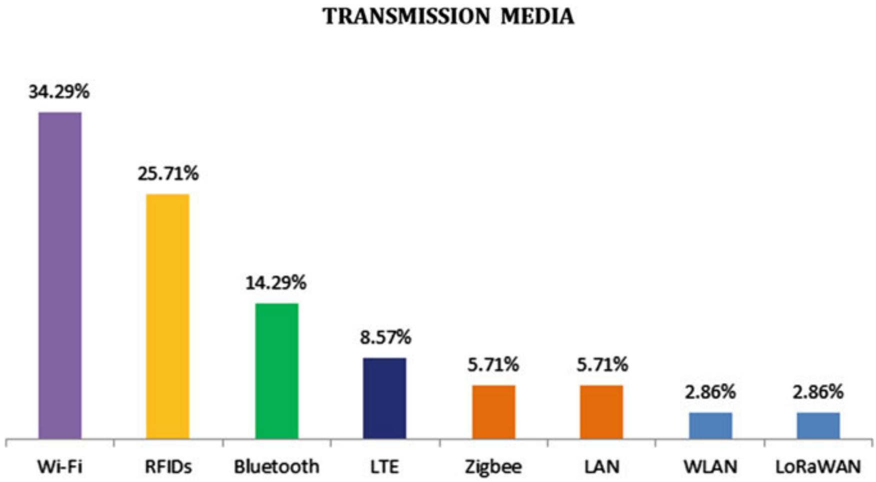

Fig. 6 Overview of transmission media

G. *Overview of Data Storage*

Figure 7 demonstrates an overview of the data storage used. The highest proportion was in cloud storage (48.15%), and the second highest percentage reported was

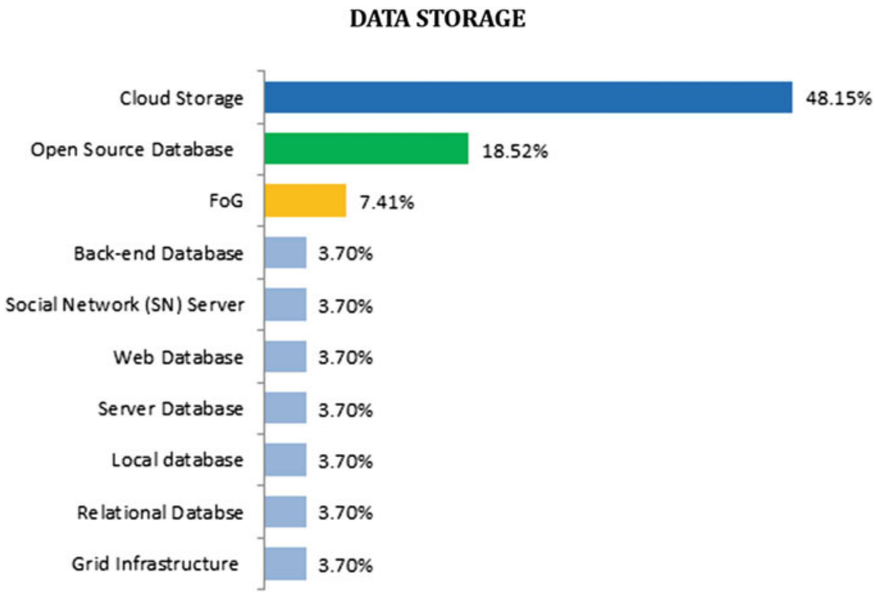

Fig. 7 Overview of data storage

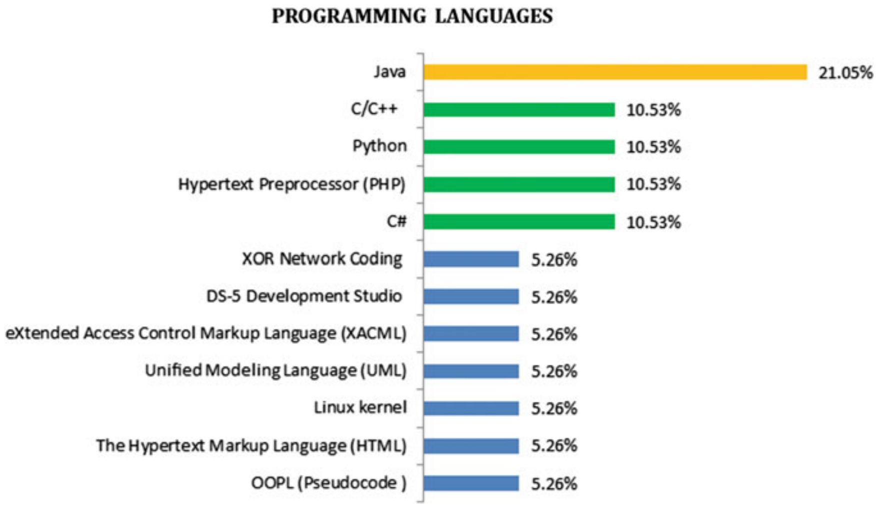

Fig. 8 Overview of programming languages

Open-Source Database (18.52%). MySQL and MariaDB were the leading enterprises open-source databases after the cloud-based database.

H. *Overview of Programming Languages*

Figure 8 represents an overview of the use of programming languages. The highest proportion was in Java Programming Language (21.05%), and the second highest reported was in C/C++, C#, Python and Hypertext Preprocessor (PHP) at 10.53%.

I. *Overview of Techniques/Tools/Mechanisms*

Figure 9 illustrates an overview of the techniques/tools/mechanisms used. The highest percentage was used in the data mining technique (42.86%), and other techniques/tools/mechanisms have been used equally.

J. *Implementation Platforms and Frameworks of Digital Health Systems*

Table 3 demonstrates the implementation/platforms and frameworks identified in digital health systems.

It can be seen from the data in Table 3 that the hybrid encryption scheme (combining both symmetric and asymmetric encryption algorithms) is adopted in digital health systems.

K. *Services/Advantages of Digital Health Systems*

Table 4 presents the application, services, and advantages identified in digital health systems.

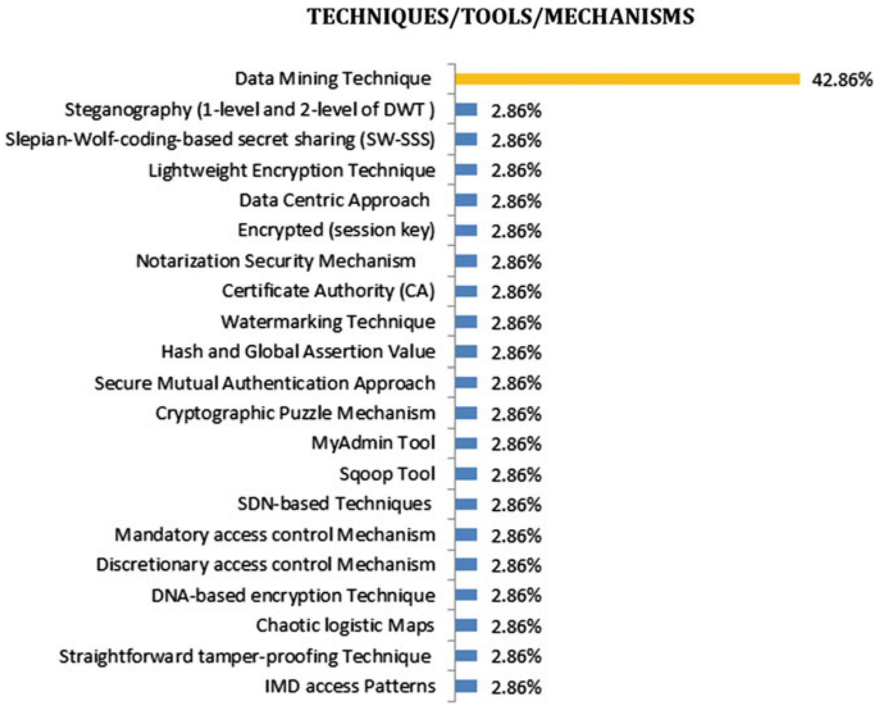

Fig. 9 Overview of techniques/tools/mechanisms

As can be seen from Table 4, new technologies and solutions are adopting gradually, the confidentiality, integrity, and accessibility of patients' medical information should be ensured.

4 Discussion

The aim of the chapter was to observe digital health systems. The data was extracted using these parameters: security issues, sensors/wearable devices, data storage, programming languages, encryption and cryptographic algorithms, transmission media, techniques/mechanism, standards/legislation/principles, methodologies/models, implementation platforms and frameworks.

The Internet of Medical Things (IoMT) is integrating devices and applications and promising to bring cost-effective solutions to health care [11]. The medical is data communicated over wireless networks with healthcare systems. Healthcare industry is endlessly producing data, and the enormous amount of medical data was collected from various forms of medical notes, medical images, insurance claims, pharmaceutical, social media, sensors, wearable medical devices and other monitoring devices.

Table 3 Implementation platforms and frameworks identified in digital health systems

#	Study	Application/model	Implementation platform	Framework
1	Elhoseny et al. [1]	Patient's diagnostic data transmission model	–	Hybrid encryption scheme
2	Luo et al. [4]	Data access control (PDAC) system	Exclusive-OR (XOR)	ID-based Signcryption scheme, ID-based Signcryption scheme
3	Al-Turjman et al. [5]	E-healthcare application system	–	Context-sensitive seamless identity provisioning (CSIP), user authentication scheme
4	Eldosouky et al. [2]	m-Health IoT	32-bit bit-sliced implementation	Hybrid encryption scheme (combining both symmetric and asymmetric encryption algorithms)
5	Tsai et al. [6]		LoRaWAN environment	Secure low power communication (SeLPC) method
6	Bradley et al. [7]	Real-time locating systems (RTLS)	–	–
7	Almulhim et al. [8]	E-health applications	–	Group-based authentication model
8	Arfaoui et al. [9]	–	–	Hybrid certificate less signcryption (H-CLSC) scheme (context-aware authentication and access control approach)
9	Varadharajan et al. [10]	–	ONO SSDN controller and open flow access points, blueprints graph API	Control plane
10	Xin et al. [17]	Multi-feature fusion recognition system	–	Multi-modal biometric recognition based on face, fingerprint, finger vein

(continued)

Table 3 (continued)

#	Study	Application/model	Implementation platform	Framework
11	Ivanov et al. [21]	Remote pulmonary monitor system (RePulmo)	CHOP	Open ICE-Lite (open-source integrated clinical environment)
12	Ullah et al. [33]	Wireless body area network	–	Secure de-duplicated data dissemination (S-DDD) scheme
13	Nausheen and Begum [20]	mHealth application	–	Obfuscation and return-oriented programming
14	Arfaoui et al. [34]	Wireless body area network (WBAN)	–	Stochastic game to balance the tradeoff between network performance and security level
15	Aydin et al. [22]	Home-based healthcare system	Contiki OS and Cooja emulator for TIexp5438 embedded platform	Secure bootstrapping mechanism (IETF 6TiSCH protocol)
16	Cagnazzo et al. [35]	mHealth application (HER/PHR)	–	–
17	Hamici [18]	E-health tele-monitoring system	–	Genetic algorithm for data security
18	Binu et al. [11]	Secure health monitoring for sports personnel (Android) application	Arduino MKRZero board	–
19	Ray et al. [3]	Remote healthcare monitoring (RHM) system	–	Healthcare plane (H-Plane)
20	Hao et al. [12]	SIoT (social Internet of things) healthcare system	Social networks (online platform)	Device-specific physical-layer (PHY)
21	Naru [13]	Healthcare system, application of IOT	–	–
22	Jaouhari [14]	E-health, Internet-integrated sensing applications	Node.js	WebRTC and WoT
23	Pulkkis [15]	Nursing home patient monitoring system	–	–

(continued)

Table 3 (continued)

#	Study	Application/model	Implementation platform	Framework
24	Mukherjee et al. [16]	IoT-based application	GENI cloud/cloud-fog communication	End-to-end IoT security middleware for cloud-fog communication
25	Barik et al. [17]	Smart health applications	Cloud-based computing environments	SoA-Fog (Service-Oriented Architecture): three-tier secure framework
26	Chiuchisan et al.	At-home health care systems	Virtual private network (VPN)	
27	Binu et al. [19]	Child health monitoring	Hadoop	Apache Ranger instead of BISE (Big Data Service Engine)
28	Nair et al. [20]	Healthcare system	–	–
29	Aledhari et al. [21]	Remote health monitoring system	SHIMMER platform	Hybrid real-time cryptography algorithm
30	Gabrani et al. [22]	Patient health monitoring system	Wireless sensor networks and grid computing paradigm	–

Additionally, the collected data is stored in cloud-based platforms or local databases which help to store and analyze the data. The patients' data includes medical data and personal information; therefore, it is essential to have standards and regulations around the world to protect the data from security issues. Regulations and standards such as General Data Protection Regulations (GDPR) [14], NIST: Next-Generation Access Control Framework (NGAC) [19], Health Insurance Portability and Accountability Act (HIPAA) [19], and Digital Imaging and Communications in Medicine (DICOM) [35] is an international standard for medical images, information, and the quality when exchanging data [37].

There is no doubt that the healthcare industry is experimenting with new technologies with the advancement of IT sector. In addition, there were some advantages as it allows healthcare professionals, healthcare service providers and patients to experience, confidentiality, and integrity of data, long-distance communication, low power consumption, improve the quality of patients' care, securing the data exchange between healthcare providers and users, provide historical and real-time data, system access control [5, 7, 13, 15, 19, 23, 24, 32]. Instead of positive factors, some negative factors have been increased, such as unauthorized access, data modification, data leaking, abuse of cloud services, inject messages to the network, interoperability of devices, streaming of huge data [5, 6, 13, 19]. The result from these articles identified that unauthorized access was the most prominent issues that most digital applications were facing.

Additionally, in health care, a huge amount of is produced. Big data is the term first informally notified by Ellsworth and Cox [38]. Big data contained 3V's: volume: the size of the data; velocity: speed of the data streaming, processing and generating; and variety: heterogeneity of data [39]. Some of the articles were focused on IoT Big medical data environment [6, 15, 36]. Big medical data can be defined as massive

Table 4 Services, advantages identified in digital health system

#	Study	Application/network	Services/advantages
1	Elhoseny et al. [5]	Patient's diagnostic data transmission	Confidentiality of patient's data High imperceptibility capacity Minimal deterioration
2	Luo et al. [6]	Data access control (PDAC) system	Secure patients' data from leakage and destruction Handling big data Storing capacity of big data
3	Al-Turjman et al. [12]	E-healthcare application system	Data conversion Spectrum sensing Digital processing Confidentiality of communicating to external devices
4	Eldosouky et al. [32]	m-Health IoT	–
5	Tsai et al. [7]	–	Low power consumption Long-distance communication protocol
6	Bradley et al. [8]	Real-time locating systems (RTLS)	Provide historical and real-time data Provide efficient asset Patients tracking in facilities Improve the quality of patient care Resource management
7	Almulhim et al. [26]	E-health applications	Offline sensing node registration Freely password and biometric update facility User anonymity and sensing node anonymity
8	Arfaoui et al. [9]	Wireless body area networks (WBANs)	Confidentiality Integrity Anonymity Context-aware privacy Public verifiability Cipher-text authenticity

(continued)

Table 4 (continued)

#	Study	Application/network	Services/advantages
9	Varadharajan et al. [27]		Secure communication between the hosts Real-time location tracking of the patients Deal with attacks on the hospital networks Differentiate healthcare related traffic Handle the complexity in the current networks Minimize the errors and enable innovation in networks
10	Xin et al. [17]	Multi-feature fusion recognition system	Reduce the influence of forged features High performance of identification Recognize accuracy Robustness
11	Ivanov et al. [21]	Remote pulmonary monitor system (RePulmo)	Analyze data in real-time Data security Guaranteed performance
12	Ullah et al. [33]	Wireless body area network	Message integrity Reduce processing and transmission delay
13	Nausheen and Begum [20]	mHealth application	Security Interoperability and performance Flexibility Low cost
14	Arfaoui et al. [34]	Wireless body area network (WBAN)	Energy efficiency Security QoS requirements
15	Aydin et al. [22]	Home-based healthcare system	Secure the communication
16	Cagnazzo et al. [35]	mHealth application (HER/PHR)	Low cost Improve the quality of service
17	Hamici [18]	E-health tele-monitoring system	–
18	Binu et al. [36]	Secure health monitoring for sports personnel	–
19	Ray et al. [19]	Remote healthcare monitoring (RHM)	–
20	Hao et al. [23]	SIoT (Social internet of things) healthcare system	Securing the data exchange between authorized healthcare users and providers

(continued)

Table 4 (continued)

#	Study	Application/network	Services/advantages
21	Naru [24]	Healthcare system, application of IOT	–
22	Jaouhari [13]	E-health system	System protects from external attacks Physical access control Protect the things from physical manipulation
23	Pulkkis [14]	Nursing home patient monitoring system	Real-time locating service to identify the location of the patients
24	Mukherjee et al. [25]	IoT-based application	Confidentiality and integrity
25	Barik et al. [10]	Smart health applications	Low-power node Reducing latency Less cloud storage Long-term storage and data analysis
26	Chiuchisan et al. [28]	At-home healthcare systems	–
27	Binu et al. [15]	Child health monitoring system	Visuospatial test Stroop test Sustained in attention blindness Child Attention Deficit Disorder (ADD/ADHD) test
28	Nair et al. [16]	Healthcare system	–
29	Aledhari et al. [29]	Remote health monitoring system	Data security Computations Low power consumption
30	Gabrani et al. [30]	Patient health monitoring system	–

datasets with complex high-dimensional diagnostic text data images [5] which can be analyzed by computers with the use of data mining techniques such as data classification, clustering, regression, association [36]. Big Data focuses on transactional data, clinical data, and social data [40]. The collected data has no meaning, and they combine with relational data such as medical history, decisions, actions, patient records to get the real meaning. On the other hand, quite a lot of challenges with big data still need to be solved by security specialists. Furthermore, healthcare industry taken some steps to enhance the security in big data, some studies have proposed solutions, such as key cryptosystem and secret sharing, implementing strong platform like Hadoop for storing, processing and retrieving patients' data [15].

The analysis of the review article has established a substantial gap in many reported articles [41–44]. Elhoseny et al. [5] work mentioned confusion among characteristics of proposed work and failed to illustrate the problem, and some works have failed to provide enough details [23, 26, 32]. Some articles mentioned assumptions that have been taken with regards to proposed work such as authentication gateway is trustworthy, social network has powerful server, enough storage, enough computational power, session keys proved the mutual authentication [12, 23]. The precise estimation of the power consumption of sensors [45, 46] would be another crucial part of the IoT stage.

In conclusion, the summary can be explained as this chapter carried out to find security issues of digital health systems and steps undertaken to overcome with them. In addition, it is observed that the new industry standard and government legislations have been implemented to ensure the confidentiality and integrity of patients' information.

5 Conclusion

Our chapter provides a review of security issues in applications, networks, data communication, and data storage of digital health systems. We have reviewed 30 experimental and peer-reviewed scientific publications. This chapter illustrated the various security issues, data storage, sensors/wearable devices, implementation platforms, and frameworks. Furthermore, we discussed the key advantages delivered from health applications. Our results show that the healthcare sector suffering data breaches for a reason for unauthorized access. However, new technologies and solutions are adopting gradually, and also international legislation is being obligated by the government to ensure the confidentiality, integrity, and accessibility of patients' medical information. It is necessary to have standards and regulation in digital health, including the Health Insurance Portability and Accountability Act (HIPAA). Artificial intelligence and robotics both are getting increasingly sophisticated in health care and has not been discussed in this chapter; health solutions using artificial intelligence and robotics along with Internet of Medical Things (IoMT) would be another avenue to investigate for future research.

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An Improvised Model for Securing Cloud-Based E-Healthcare Systems

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1 Introduction

In cutting edge innovation, the use of the distributed computing for sharing and conveying assets among numerous establishments and people has met an enormous embracement. Since it encourages the asset sharing administrations, for example, (servers, stockpiling, systems, and applications) by offering an easy to understand detail and a cloister use, fundamentally there are two sorts of cloud frameworks open and privet. Where the open cloud furnishes off-site arrangements with many facilitating models, for example, stage as an assistance (SaaS), infrastructure as a help (IaaS), programming as a help (PaaS), and information as an administrations (DaaS). Instances of the open cloud are Google Application Engine and the platform such as Windows Azure Services Platform [1]. While, the private cloud adopts another strategy as it is devoted to a solitary association and its servers are either

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_14

at off-site or inside the premises, and private cloud is more made sure about and have better customization that the open cloud, instances of private cloud are Cisco, Dell, HP, and IBM. The process described above changes over records mentioned on paper into digitalized system of electronic records, for various applications, such as electronic medical records (EMR), electronic health records (EHR), personal health records (PHR), and electronic health data (EHD). Further, the application of EHR and EMR are perfectly fine records of patients that dealt by technical known as healthcare services professionals, whereas the application PHR transports individual data which is acquired by and proven either by understanding or their family members all the time. EHD as electronic well-being records or mechanized patient records is an organized assortment of savvy well-being records of patients. Healthcare associations will in general have a couple of qualities that make them appealing focuses for attackers. A key explanation is the quantity of various frameworks that are not fixed consistently. Some of them are installed frameworks that, because of the manner in which the maker has made them, can not be effortlessly fixed [1, 2]. The quantity of e-health records is increasing at an alarming level and it essentially required to be retained in an efficient manner. Each of the restorative records comprises of texts, images, and graphs. Thus, each of these records is in unorganized form. Despite the fact that the EHRs are exposed to different difficulties regarding protection and unapproved get to, the most unmistakable one is relating to information protection and security. Dangers fluctuate from the malware assault that bargains the respectability and confidentiality of clinical information Hence, cloud computing provides us through a viable solution with an advantage of scalability, storage, and security. The main objective of the chapter is to provide analysis and concerns of cloud computing in healthcare devices. The chapter provides the proposed framework with assistance of Google Cloud Healthcare API and GPS for area following of patients. The chapter also discusses the impact of different data breaches and other security issues in the healthcare sector. The chapter is the conglomerates the prevailing concerns with healthcare devices, perturbing the existing applications of cloud computing in the healthcare sector. The research methodology proposes the framework for implication of Google Cloud in Health care and in the later section improvised method to compare current framework are discussed with the proposed framework and further summarizes the chapter through discussion section.

2 Prevailing Concerns with Healthcare Devices

Despite the gargantuan and plethora of advantages for healthcare consumers, e-Health possess a new challenges and threats to their privacy. Many of the users of e-healthcare system are not nuanced with the facts that their use of the healthcare resources might be followed in the cyber places. Consumers might also not be aware of the fact that their personal information might be accumulated to the databases each time they browse a Web site [3].

Fig. 1 Conglomerate shows various facets of security challenges

The repercussions which are drawn from the analyses of privacy policies manifest a gargantuan of common privacy concerns. There are different kinds of healthcare devices which are presently marketed one of the categories of wearable devices. Which are used very commonly by the population of different demographic factors and the number of privacy issues is highlighted [4]. The vitality of guarding the privacy of e-healthcare system users is investigated and emphasized "the portion of population which has implication of Internet for health associated concerns have rights to anticipate the protection of personal data" [5].

The concern of medically relevant and generated data has another aggregation of problem which is associated with the process of transmission of this sensitive data. The healthcare data is an alluring target for the hackers. It is often to see cybercriminals to invade and exploit the data as per their own will and wish [6, 7]. This fraudulent breach of data has apprehended in last year. Therefore, the protection of healthcare system data is a humongous deal and it should be seen as the elementary motivation for the healthcare devices providers to take care of it. The challenges associated with the security of healthcare devices are depicted in Fig. 1.

2.1 Data Privacy

Medically associated data poses an enormous number of questions, particularly, with regards to the ownership. The data gathered from users is times guarded as their own only and exclusive property in case of various wearable healthcare devices like BASIS's products [8]. While certain other brands from the plethora of wearable healthcare devise such ad Fitbit keeps the rights reserved for the purpose of use and commercial exploitation. All data submitted during the purpose will have no rights of privacy over it [9].

The very obvious question which is birthed from these researches is whether or not healthcare devices comprise of the personal data? As it is very exclusive in nature; although that might not be significant recognizing the identity of the user. Therefore, securing and keeping the data obscured requires the high protection levels for the e-healthcare sector. This implies the security essentialities and privacy concerns are conceded and structurally analyzed for the pioneering of system designing. For a trustworthy and robust structure of system and the distinctness, there is a four e-level approach suggested: (A) Deciphering the system and conceding the participants of e-healthcare scenario as the attackers into the account; (B) conduct an evaluation for the threats concentrated on STRIDE for a structural and wholesome analysis of threats; (C) to formulate the implication of case-specific security requirements along with the security concerns addition to the respective relevance; (D) elimination of threats by formulating what all countermeasures are to be adopted [10]. Also, ensuring the anonymity data associated with the medical fields is must/may have sensitive information about the patient and therefore it should be kept discrete in overall network. For keeping the data discrete, lightweight ring structure is also suggested along with the incorporation of the digital signals and no one (instead of the one with actual signatures can use the message) [11].

2.2 Decentralization

In order to commit robust and to yardstick and to mitigate multiple-to-sole traffic rows, there is an imperial need to develop a decentralized system. This kind of system will help in dealing with the major drawback of information failure or delay problems. The model with the decentralized system has been proposed in many researches.

2.3 Authentication

The data received from the cloud or user's computers or devices used in the healthcare system maybe existing in the form of unprotected data. During the process of transmission that data might be lost. Therefore, during transferring of data, the modification or alteration in data is possible along with the possibility of permanent loss. The conservation of this incorrect tampered data maybe an additional burden. In cases of monitoring devices administered for the patients treatment, this loss of data may lead to a loss of lives. Consequently, to ensure the safeguarding of this critically derived data, it is suggested to use the *lightweight digital signature* scheme [11]. On the receiver's end, this data is authenticated with the help of user's digital signature. If the transmission was correct and the data is correct, it makes it is pulled properly and a receipt is sent to the sender regarding the same.

2.4 Measurability

Providing a solution to the PoW is a computationally exhaustive work; IoT devices which are commonly used in the monitoring systems are constituting of multiple nodes and scaling of blockchain happens poorly as the number of nodes in the system increases. Thus, it can aid to suppress or completely eliminate the concept of

PoW in the entire blueprint of networks and the overlay can be bifurcated into several small clusters in the network instead of one single blockchain being use. Thus, one single blockchain would not be responsible for the entire nodes but will have several nodal clusters. There are models being proposed which can be used as because of their distributed nature and higher security properties to the network [12].

2.5 Data Storage

The storage of loT big data by the implication of technologies like blockchain is a cumbersome task and may lack practical significance after an extent. Therefore, the aid of cloud base serves to store the data is encouraged. This has to be conducted in the forms of encrypted storage data blocks. The data safety is over the cloud is guaranteed by the use of another additional layer of cryptographic security which functions alike a digital signature and uses high standard encryptions. In order to complete the purpose, it is suggested to use the transactions in distinct blocks and create the combined hash of each block using Merkle Tree and then the transmission is carried to the different blocks. This manner, any of the alterations in the cloud data can be screened and scrutinized easily. Conducting the storage in this fashion will conserve the decentralization of data to a certain levels.

There is a lot of jurisdiction involved in with the storage of medical data—the use of wearable healthcare devices such as BASIS, Jawbone, Nike+, Fitbit—has declared that the data will be stored in the out with the European Union (that is specific and is commonly related with the use of the stronger protection for the user private data) [13]. Nike+ did declare that they would not be transferring data without the Nike group, unless necessary the purpose of the service processing [14]. Also, quoting the relevance of the Safe Harbor agreement, between the USA and European Union, which is an outcome of the voluntary process through which is to ensure that brands from US are maintained the standards set by the European Union. These elementary necessities state that “Under the directive, companies must allow the consumers to use their data, nuancing its origin, appropriate and updated information, without allowing the use of data by unauthorized uses and take legal recourse for unlawful processing of the personal data” [15]. Nike+ and Fitbit allow the compliance to this agreement but Jawbone and BASIS have no statement for it.

2.6 Security of Data

The data generated and recorded from the medical devices and health care must be appropriately accurate and should be designed in a manner that it cannot be manipulated or exploited by the hackers invading in the system. Techniques driven from cryptography are aiding the exchange and transfer of information in secure and confidential manner [16]. Use of the double encryption technology scheme is suggested with the high thrust. Here, the meaning out of the double encryption shall not be at conundrum with same data being encrypted with the two keys but instead encryption with the encryption of data which is present in the encrypted manner. Lightweight ARX algorithms are recommended for initial encryption and then deploying of encryption keys for public key of the receivers. Also, the suggestion is drawn for the use of the Diffie–Hellmen key exchange techniques for conducting the transfer of public keys, thus, it reduces the chances for the invading and getting the key [12].

3 Related Work

As indicated by the World Health Organization (WHO), e-health can be described as the process of utilization of information and communication technology for health care. There is a need to secure, store, and maintain the personal health information (PHI), cloud computing and healthcare cloud services are capable of storing data significantly particularly when it comes to large image files which is very common in healthcare sector. The collaboration of cloud computing and health care has a huge potential to improve a host of healthcare-related functions such as telehealth and virtual care, medication adherence, personal data privacy, and the uniformity of medical records.

Through telemedicine, such information can be collective among healthcare experts and patients who probably would not originate in the equivalent physical area. The health statistics are developing at an exponential rate, the bases are showing restraint's individual records, data structure experimental preliminaries, and genomics arrangements data [16]. Also, as per the other researchers, some of the preparing stage is as follows, i.e., Hadoop Framework and Amazon EC2. Besides this, there is likewise a requirement for enhancement of adaptable framework that gives a continuous development of correspondence among medicinal services the board framework and clients getting to it. Biomedical data allocation is an additional territory where cloud computing is picking up ubiquity for agents to share data however includes dangers like information misfortune and unapproved access to information. There are various meanings of the cloud and the huge showcasing activities have to some degree obscured the real factors of what cloud computing is. The cloud is considerably more than only a monetary model. Cloud advancements can be conveyed in various manners and in different configurations [2, 17].

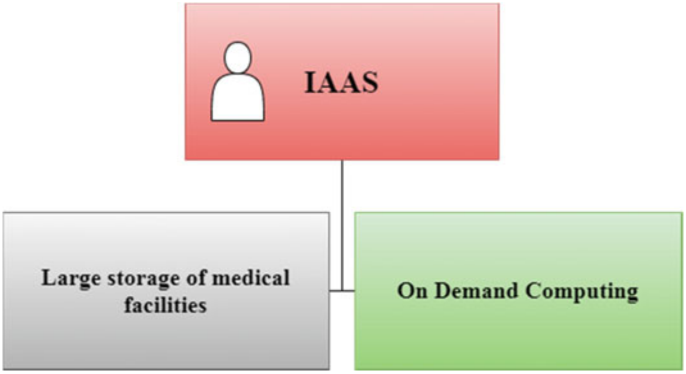

Fig. 2 Infrastructure as a service

3.1 Delivery Models

3.1.1 Infrastructure as a Service (IaaS)

IaaS provides a connection through the foundation expected to retain its business. This may incorporate systems, figuring assets, for instance, servers or capacity, and staffing mastery. Generally, in these cases, the controls of the working framework, functions, and systems are being done by the association as shown in Fig. 2. Also, it is being examined a medical clinic may utilize the cloud for indicative imaging calamity rehabilitation. The office has its individual PACS and file, yet it buys space and system administrations to highway a duplicate of information to the cloud supplier if there should arise an occurrence of lost information. The cloud specialist co-op has slight teamwork with everyday occasions at the clinic and access to this information is limited to case by case evidence notwithstanding calamity [18, 20].

3.1.2 Platform as a Service (PaaS)

The delivery method of (PaaS) is an assistance model in which the customers directly deal with the applications sent and not the fundamental framework. This is done because of programming applications where specialists approach advancement instruments, databases, and middleware just as foundation programming. Medicinal services suppliers with IT advancement staff may use this model to build up a nearby microelectronic clinical proof (see Fig. 3).

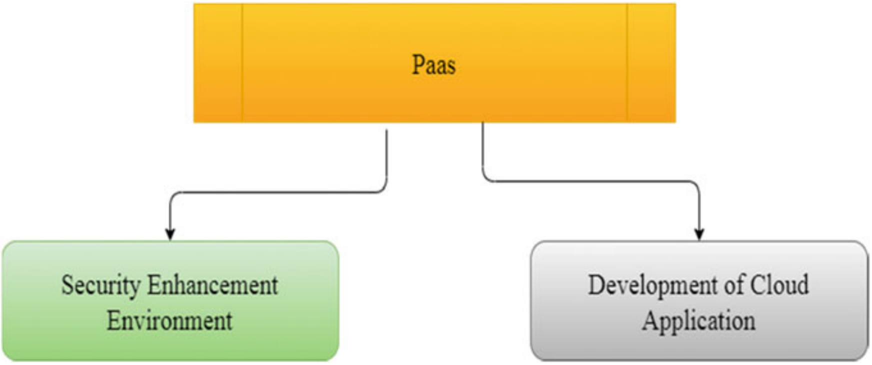

Fig. 3 Platform as a service

3.1.3 Software as a Service (SaaS)

This delivery model SaaS turns into a model that deals with human services suppliers to promptly receive new innovations without inordinate capital expenses or preparation endeavors, and it is represented in Fig. 4, SaaS provides customers with remote access to the application. This is typically through an Internet browser. Offices

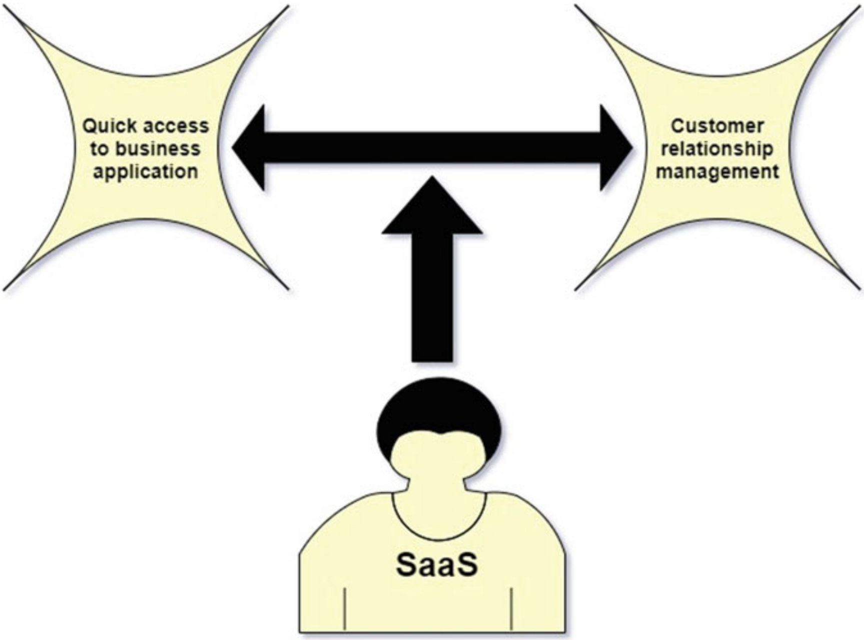

Fig. 4 Software as a service

need not stress over capacity or application, the panel as just explicit parameters are empowered for the client. SaaS can be immediately sent and used without the requirement for any capital costs, accomplishing extreme uptime, and advantage from the innovation.

3.2 Analyzing Existing Problems in Healthcare System

3.2.1 Compliance

Medicinal services IT's greatest concern is compliance. Human services compliance disputes can affect each sort of clinics, paying little mind to the size. Social insurance establishments of smaller or larger sizes the are required to adhere to a specific arrangement of guidelines and administrations to accommodate to government oversight and guidelines. To avoid damage's direction, all associations ought to be comfortable and agreeable with changing social insurance patterns, rules, consistence laws, and government guidelines. To limit their obligation hazard and government examination, you may consider a clinical consistence plan or advising a consistence official. The job of a compliance official in medicinal services is to guarantee your clinical practice holds fast to all arrangements and rules and will execute change when a training is resistant.

3.2.2 Information Protection

Securing information in the human services industry is no simple accomplishment, human services suppliers and their business partners must adjust ensuring the secrecy and security is achieved while conveying quality patient consideration and meeting the exacting administrative prerequisites set out by HIPAA, this is represented in the above given Fig. 5. There are various ways through which the data from HIPAA is breached. There can be one or more ways for the breach of data, the drainage of data accruing in conjunction with more than one way is combinative data drainage. Different guidelines are described, for example, the EU's General Data Protection Regulation (GDPR). Since ensured well-being data (PHI) is among a person's generally delicate (and for crooks, significant) private information, the rules for healthcare providers and different associations that handle, use, or transmit tolerant data incorporate exacting information security necessities that accompany weighty punishments and fines in the event that they are not met [19, 20]. As opposed to ordering the utilization of specific advancements, HIPAA requires secured elements to guarantee that understanding data is secure, open just by permitting people, and utilized uniquely for approved purposes, yet it is dependent upon each secured substance to figure out what safety efforts to utilize to accomplish these target.

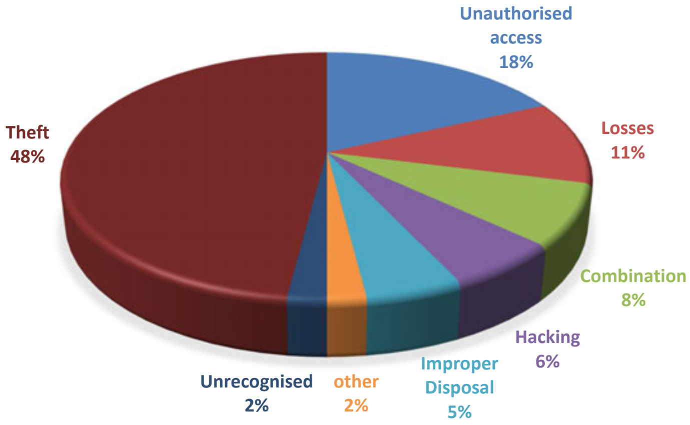

Fig. 5 Types of data breaches by HIPAA

4 Research Methodology

4.1 Analyzing Existing Framework

The existing framework work has few limitations. Based on the process in which the customer side, RIA authorizes the customers to cooperate by the system. RIA is composed of script language codes to execute strong UI display for Web users. Since smartphones are becoming available everywhere, these applications can interact with cloud as well. Secondly, the cloud server is clarified either manages the database through Amazon's Simple DB or follow. Also, it will present the stage for community and companies to combine their approvals with the system. REST is utilized to found the link or interface among RIA user and cloud server. Thirdly, the application part works with client and server that can execute essentials for the entire framework. Furthermore, this layer is continued to some functioning rules such as information security, Web functions, exchange data, and application query. The government ministry will handle the management of this layer from upper level with its own particular interface. The outsiders linked with clinical services like protection, pharmaceuticals are likewise added with the cloud by means of this layer. Here, the outsider affiliations are protected and refreshed by the chairman. Significant bit of clinical data can be separated from the cloud storehouse which has a broad incentive for development of e-health framework. It is expected that electronic health records (EHR), personal health records (PHR), and hospital information systems (HIS) more likely to have dedicated servers/virtual machine servers and are to be facilitated in the private cloud. The flow of architecture is described in Fig. 6 which helps in understanding the process. Also, the few limitations of the existing structure have been improvised in the improved model. The PHR will have data identifying with the consideration of a patient. Doctors are to give patients admittance to their clinical

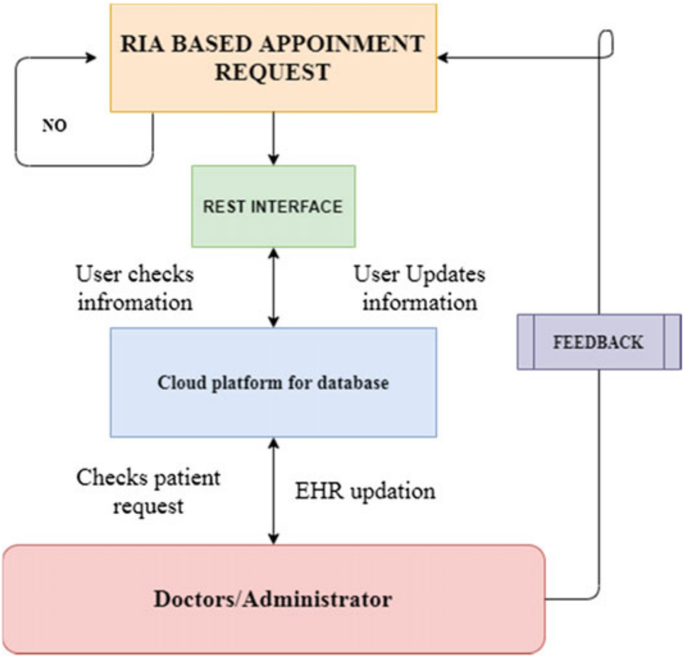

Fig. 6 Data flow diagram of existing framework

proceedings in order to authorize them to store them in their PHR accounts. Patients are given the selective option to keep up the information in their PHR accounts accordingly any adjustments in their health can be transferred to their PHR accounts [21]. They may subsequently make their primary care physicians aware of their PHR upon approval for the vital exhortation. Also, HIS is the third and last assistance to be facilitated in the private haze of our model. It will have information and administrations, for example, administration, medical charging and health insurance, personnel and arrangements, planning, budgeting, general clinical specialist data, distributed interview between clinical officials, and so on.

Web-based requests are being worked with the utilization of present day distributed computing to build a three-level e-Health Cloud, cloud computing interacts with RIA, Web administrations, REST, and Simple DB. A facility is a set of business capacities and usefulness that associate with requests by means of interfaces. In figuring, administration implies data or usefulness which serves the applications and the administrations do not interface with human rather servers and requests. In any case, SOAP is the convention for customary SOA which is not Web situated. Though, REST is the contending innovation to use for online frameworks [22]. Hence, in this improvised model, the concept of the REST takes place and being utilized as the administration arranged engineering for e-Health Cloud. Illustrative State Transfer (REST) is a product design for disseminated frameworks like Web. The World Wide Web (WWW) has transformed and embraced new highlights with the evolvement of Web 2.0. Web accessibility is presently extending wherever through broadband, Wi-Fi, versatile Web, and rustic zones. The functionality of the REST is intended for Rich Internet Application (RIA) on Web 2.0. REST that has picked up a notoriety for its straightforward interface and light-weighted conduct. All the information and functionalities in REST are considered as assets. The identification of assets is done by Universal Resource Identifier (URI) exhaustive which well-defined events are performed to set up a stateless correspondence convention, for example, HTTP. Information trade is made simple with XML or JSON with a compositional structure of customer server worldview without extra informing layer. The rich customers cooperate basically with the server [23, 24] through HTTP which wipes out the utilization of SOAP. Relaxing applications are elite for its flexibility with other Web 2.0 parts. In this e-Health Cloud design, the steady correspondence between the RIA customer and simple DB-based cloud server is done by REST. e-Health Cloud will convey APIs to outsiders to recover and refresh EMR by means of REST.

4.1.1 Simple DB Cloud

Simple DB is a cloud-based database administrations gave by Amazon. Also, the Web applications can store information, track inquiry, or procedure information on simple DB. The office is: there is no weight of blueprint upkeep, gathering, or other authoritative technique on information [20]. The engineers just utilize the cloud stage for database the board and pay on precisely the amount they use. Any center information activity, for example, questioning on organized information can be performed by the use of cloud platform. EST is utilized for the information access on simple DB. It lessens unpredictability and APIs can be utilized to access on database from different applications [22].

5 Improvised Methodology

5.1 Current Framework

Based on the limitations of the existing framework, the current framework limitations are taken into consideration and an improved model is structured over past medicinal services models. Table 1 compares the existing framework with the improvised table based on the parameters API, security, performance, and data management. It has consolidated all the fundamental parts of the medicinal services framework together that are patients, specialists, indications, and diseases. This improvised model incorporates and highlights the Google Cloud Healthcare API and furthermore GPS for tracking the location of patients. The stage likewise offers help for social insurance information norms, including HL7, FHIR, HL7 v2, and DICOM, just as computerized DICOM and FHIR de-recognizable proof to all the more likely plan information for

Table 1 Comparison of the existing and improvised framework

Parameters	Existing framework	Proposed framework
API	REST API	REST API, DICOM API, HL7 API, FHIR, API
Security	Low because of no added security other than IAM	High because of de-identification is available with IAM
Performance	Low because of no added features	High because of embedded location tracking system and AI
Data management	Not adequate	Managed with the help of Big Data

these platforms [22]. AI will enable suppliers to interface with information utilizing Web-accommodating, REST-based endpoints for medicinal services to be adaptable and investigative as per needs. In a push to address information security concerns, Cloud Healthcare API identifies touchy information in DICOM cases and FHIR assets, for example, ensured well-being data, at that point utilizes a de-distinguishing proof change to veil, erase or in any case darken the data. Cloud Healthcare FHIR API the rising standard utilized for trading healthcare data. Cloud Healthcare HL7v2 API prevalently received a technique for the combination of well-being systems. Cloud Healthcare DICOM API are useful for imaging-related and radiology disciplines. It is smarter to utilize Google Healthcare API from the current Cloud Healthcare arrangements because of the four components that additionally go about as the four mainstays of the Google Cloud.

5.1.1 Powerful Analytics

With the Big Data instruments that accompany Google Cloud Platform, one can process over petabytes of human services information at a lightning speed [21]. You can change over the immense measure of imaging, genomic, clinical, and the protection information into clinical industry forward leaps, propelled care, and smoothed out activities through the Google Big Data offering.

5.1.2 Machine Learning and AI

While AI has just demonstrated itself to be the pattern changing health care, with GCP, you would not need a huge group to get the most understanding out of your information. You will get a few pre-prepared models that permit you to characterize recordings and pictures and take out data from a large number of overviews and articles. You can even create redid models through TensorFlow and Cloud Machine Learning Engine to run or scale your models.

5.1.3 Associated Care

With the patients' requests getting slanted toward consistent consideration, information interoperability has gotten more essential than any other time in recent memory. This rising interest for interoperability has brought forth gauges like HL7v2 and FHIR which sets out the premise of information move starting with one machine then onto the next.

5.1.4 Coordinated Effort and Mobility

Regardless of whether the patients and partners are in an alternate room or in a different piece of the world—with G Suite, the cloud-based efficiency apparatus which underpins all the HIPAA compliances, all of you can stay associated. G Suite permits the partners to trade private clinical data while guaranteeing secure telemedicine meetings through Hangouts Meet.

Figure 7 depicts the architecture of the improvised framework. Firstly, user/patient can get to the Google Cloud Healthcare API and enters the side effects and his area [23]. The lateral effects are mainly the clinical problems that are being deteriorated by

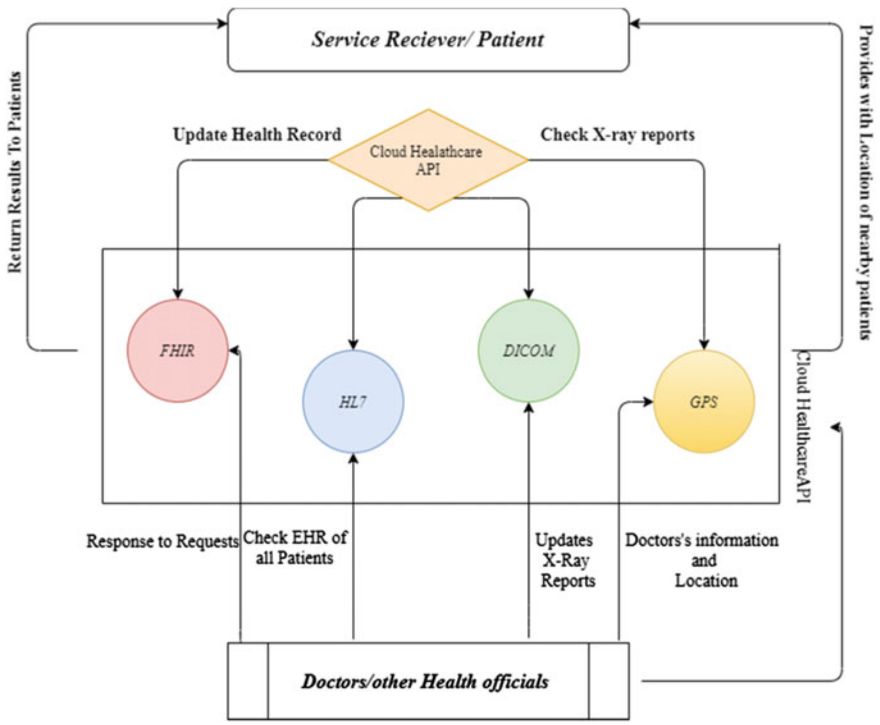

Fig. 7 Data flow diagram of improvised framework

the client over which he expects a treatment. This data is put away in the HL7 which contains all the EHR for patients. Based on the indications entered by the client, it shows the closest particular specialists and emergency clinics concerning the client's area with the help of GPS installed in the system. The framework investigates the EHR in HL7, then it maps the coordinated malady with the specific specialists by procuring subtleties from database. HL7 are a lot of worldwide measures used to move and offer information between different social insurance suppliers. All the more explicitly, HL7 helps overcome any barrier between healthcare IT applications and makes sharing medicinal services information simpler and increasingly productive when contrasted with more established methods. Patients frequently have more than one specialist or may visit the ER once in a while, yet they cannot heft around their whole healthcare record with them. Gauges like HL7 make more information accessible to doctors helping them settle on better choices and all the more proficiently give the best consideration to their patients [24]. Client/patient can choose a specific specialist or a medical clinic and book an appointment. To book an arrangement, the client can get to Chiron the other hand, specialists can either acknowledge or terminate the arrangement and an affirmation is shown to the client as needs be. The Digital Imaging and Communications in Medicine (DICOM) is a global standard utilized for clinical pictures, for example, X-beams, MRIs, ultrasounds, and other clinical imaging modalities which can be accessed by patients to see their reports and by the human services suppliers to update information [25, 26].

This is the improvised framework of e-health care the board framework with assistance of Google Cloud Healthcare API and GPS for area following of patients [27, 28]. It is analyzed that the Cloud Healthcare API gives a pathway to savvy examination and AI abilities in Google Cloud with pre-constructed connectors for gushing information preparing in Dataflow, adaptable investigation with Big Query, and AI with AI Platform. It guarantees improved productivity which is relied upon to encourage trade of healthcare data and simultaneously diminishing healthcare costs. Likewise, it builds nature of care and security for tolerant by methods for upgrade of value and amount of data. This model assists with arranging records like remedy and reports, for example, X-beam brings about cloud. Moreover, it takes out keeping up discrete records [25]. The patient administration framework configuration worried with medical coverage office gives segment sets up the most extreme presentation for activities of healthcare coverage.

The requests for improved framework proceed to increment and are not prone to back off. With the present form of medicinal services and the several selection trials that it faces, it is intelligent to presume that cloud innovation will be at the bleeding edge of social insurance development. Government motivators for electronic healthcare records selection, digitization, and bringing down costs will necessitate that cloud innovation (or some type of what we know as cloud innovation today) become more standard [29, 30]. Cloud providers are exceptionally mindful of the impediments to reception and will work to defeat these huge difficulties through instruction and verification of ideas. In the long run, recognitions that exist today will be improved. Envision a framework where persistent data is open from any cell phone in a protected and private way. The whole patient record, united into a solitary view from any number of various applications, gives exact and modern data whereupon doctors can settle on better educated choices. Centers, clinics, protection payers, and patients are for the most part ready to get to the significant data varying. Electronic health records, computerized clinical imaging, drug store records, and specialist's notes are completely combined and open [31, 32]. The capacity of specialists to run investigation, better treatment alternatives, ideal protection programs, and the potential outcomes of genuinely customized human services have become a reality. Also, social insurance supplier IT offices can offload the weight of overseeing framework and spotlight on supporting increasingly quiet consideration-related exercises. New advances can be immediately assessed for their viability and conveyed extensively from a cloud model, permitting human services suppliers to remain side by side of the best in class apparatuses. At last, persistent consideration will improve, which thus will drive down expenses and improve efficiencies [33]. Cloud innovation will be a main thrust in the human services biological system for a considerable length of time to come. The option is bankrupt offices, healthcare costs that skyrocket to unreasonably expensive levels, and patient consideration conveyance that depends on an obsolete and wasteful framework.

6 Conclusion

In this chapter, there is diligent emphasis given on the various concerns associated with the medically generated data, jurisdiction involved in the use of fitness brand-related data. The security concerns for the storage and transmission of the medically generated data is conceded. Also, this chapter also analyzes the existing framework challenges associated with it highlighting the need for improvised framework. Moreover, this document provides underlined vitality of medically generated data and security concerns associated with it. Systemic discussion about the concerns and challenges of the existing systems is being applied. Taking that as the background, the framework is proposed to substantially mitigate the challenges and scope for future investigations that can be conducted in this arena are highlighted. This work encompasses the information about the implication of the cloud computing in healthcare system which is a newfangled and state-of-art approach of computational intelligence in health care. The pioneering of technological researches in the healthcare domain is an imperial need and there are excellent examples of this amalgamation being explored.

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Human-Centered Design Smart Clothing for Ambient Assisted Living of Elderly Users: Considerations in the COVID-19 Pandemic Perspective

Sofia Scataglini and Silvia Imbesi

1 Introduction

The relationship between Design Research and older users has been deeply improved during the last decades [1] in the light of the worldwide constant growing of the average age of the populations, especially in the most developed countries [2]. The aging trend brings with it deep changes in the social scenarios across the world, regarding primarily the fields of social welfare and health assistance that require a continuously increasing engagement of the public and private sectors to conceive new assistance and welfare tools to guarantee fair and healthy aging to the largest possible amount of people all over the world [3]. Design Research is widening its boundaries to express its dimension related to the social improvement in different fields; in the light of the current scenario, one of the most significant and promising applications is Design for the Healthcare practice, a field where design becomes the interface between people and innovative technologies, combining multidisciplinary contributes to empower the user's autonomy, monitoring health status and well-being improving quality of life [4]. The application of the design principles in the healthcare sector seems to be a promising tool to optimize strategies and investments, making them properly feasible and effectively responding to patients' needs [5].

Design Research has always had a deep connection with the detection and satisfaction of people's requirements, even if they were belonging to small niches of

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_15

users characterized by specific peculiarities not common to the rest of the population. Within the Design Discipline, there are many possible approaches to empower the design process to gain a more effective response to users' needs and improve their quality of life, and one of the most popular and experienced ones is Human-Centered Design (HCD), developed to be an approach on problem-solving that involves the human perspective in each stage of the design project [6]. Literally cite the current standard, "*Human-Centered Design is an approach to interactive systems development that aims to make systems usable and useful by focusing on the users, their needs and requirements, and by applying human factors/ergonomics, and usability knowledge and techniques. This approach enhances effectiveness and efficiency, improves human well-being, user satisfaction, accessibility and sustainability; and counteracts possible adverse effects of use on human health, safety and performance*" [7].

Transposing this concept to the field of design for the elderly, HCD allows in developing design processes that consider the affections of the older person's performances as invariants of the project, not making those a responsibility of the final user. To make the described approach, it is often accompanied by co-design, a design tool useful to directly and personally involve the users in the whole design process, making them active participants to the project and designing with them instead than for them [8]. The great importance of the users' involvement in design project has been investigated from many perspectives and the co-design tool tries to explicit the good practices that can improve the results of the process by engaging the user in every single stage and collaborating with him for the definition of objectives and requirements, for the prototyping and testing phase, and in all the iterative design process phases [9].

The current technologies have a central role in developing human-centered solutions: their constant evolution creates continuous new possibilities of application and technology transfer. The concept of Internet is evolving from "a network of interconnected computers to a network of interconnected objects" (European Commission 2009), giving birth to the Internet of things, a platform including daily objects, devices, environments, and services. A growing portion of the IoT is dedicated to consumer applications, especially regarding the smart home, making possible a connection between different devices to help the user in improving his status of health and well-being. Referring to design for aging people, the Internet of things gives to designers a huge amount of new possibilities in creating smart solutions for the daily monitoring of the person in the daily environment, and the choice of a human-centered approach in those typologies of design projects seems to be useful in the expansion of the effectiveness of the conceived design solutions and addresses to specific users [10].

Based on the previous consideration, this chapter aims to study and discuss the current smart garment technologies based on HCD approach for Ambient Assisted Living (AAL) for monitoring and improving life quality, lifestyle and health of elderly users looking to the impact of the coronavirus (COVID-19) pandemic.

2 COVID-19 and Human-Centered Design for Older Users

Something tragic and unexpected has happened in recent months that has challenged many of the assumptions which are on based the current research practices related to the field of design for older people: that was the COVID-19 pandemic which has spread dramatically throughout the world, putting the current system in crisis in many different sectors.[1]

The HCD practice and the co-design tool, applied to the design for the aging field, have always been based on several assumptions on needs and requirements taken as invariants for all the projects addressed to that typology of users, regardless of whether the projects concerned devices, services, or processes. Those assumptions are the ones regarding culture, personal status, diffused pathologies, daily habits, statistics on preferences, etc. Today, unexpectedly, the COVID-19 disease has deeply changed our society affecting our daily habits, instilling new fears, modifying the relationship with other people, and changing the perception of public and domestic environments. Those new feelings determined changes in human relationships, routines, future programs, and expectations creating a new context, with new rules and new ways of interaction between the person, the objects, and the environment.

Particularly, in Europe, elderly were the hardest hit category because of their past pathologies that made them more vulnerable to the virus, and in many cases because of their necessity of personal assistance or hospitalization, which makes them more exposed to contact with healthcare professionals who may have been infected by other patients. The previously achieved balanced condition between the typical diseases of old age and good quality of life is today questioned by the current context [11].

Regardless of when the situation will be resolved, and we hope it will happen as soon as possible, it is not too early to notice that that event's consequences will significantly impact on the world's balances even in the medium and long-term perspective.

Containment measures taken to combat the virus, such as the mask and social distancing, have given rise to new behaviors, new ways of interaction and new reasons of satisfaction and frustration. The paradigm in which we operated has profoundly changed and requires today to be read again and interpreted especially concerning the requirements of users as the elderly. In HCD, we used to explicit requirements and collect needs to set the project's specifications: We used to analyze project invariants related to issues regarding available technologies, ergonomics, biometrics and all the information on the user category that is deductible from his targeting; and combine them with the project variables, determined by the personal goals and frustrations, the specific physical and health conditions, habits and preferences of the specific user. Both human project invariants and variables were then summed to obtain the human project specification. COVID-19 is challenging our usual practices because as our basic assumptions seem to be less effective: There is

[1] https://www.who.int/health-topics/coronavirus#tab=tab_1.

much information we used to take for granted that today are not reliable anymore, requiring the hardest work of collection and interpretations of the human diffused and personal behaviors.

Just to make some examples, here are some statements that could be taken as granted before COVID-19 but now are not so reliable; the statements are referred to older users living in their own home and not needing constant assistance from a caregiver[2]:

- Older users need to frequent their relatives as much as possible, especially the youngest ones.
- It is good for older users to attend different places to socialize and interact.
- Older users need to carry out different activities independently, to decide their favorite lifestyle feeling autonomous.
- Traveling, meeting new people, and undertaking new hobbies are effective stimuli to keep the person active.
- Personal assistance always reassures the elder's relative on his safety condition.
- The older person needs to go regularly at his doctor's office for effective monitoring of his health status.
- It is useful for the older user to be involved in each stage of the design process.
- The best strategies to collect the needs of a specific user are to interact with him in person.

In the light of the pandemic, those statements, that before were human project invariants, today shift to the list of the human project variables, which the designer and the multidisciplinary research team need to investigate project by project referring to a specific context and a specific group of users, because Design Research literature referred to COVID-19 now is not yet exhaustive enough to suggest good practices for HCD processes (Fig. 1).

3 The Impact of COVID-19 in Ambient Assisted Living (AAL)

As we can say that the virus has removed certainties from many established practices, so we can assert that it already suggests new certainties about what the post-COVID-19 world will be. It is already pretty obvious that public investments on health and welfare tools will be empowered that hospitalization modalities need to be rethought and that the personal assistance for the elderly could be not as safe as it should be.

The authors work in the field of HCD for AAL that is now facing the impact of the virus on its methodologies on design processes.

[2]The statements were collected in the PhD research of Silvia Imbesi, "Inclusive Design for the elderly".

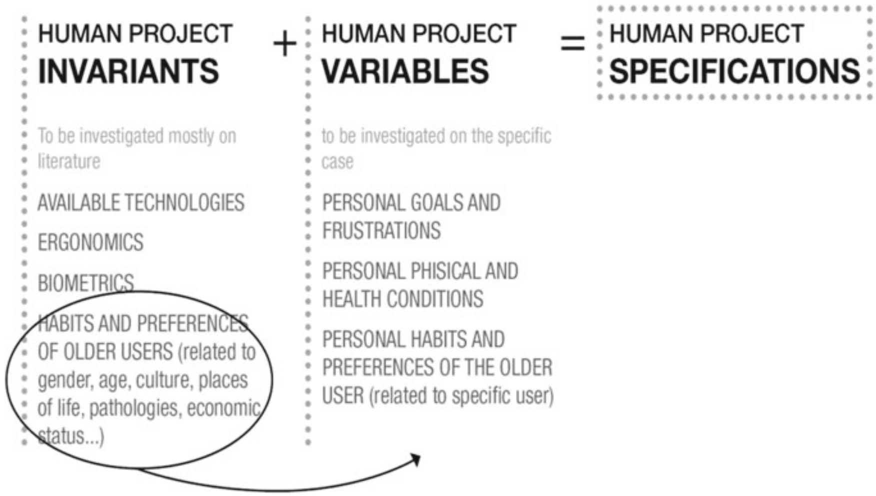

Fig. 1 In the scheme are listed some human project invariants and variables that combined generate the human project specifications

AAL involves the use of smart devices, wireless networks, software applications, computers, and sensors that, thanks to the Internet of Things, modify the user's environment to make it safer, healthier, and more adaptive to the specific person's needs. The possibility to transform the place where the user lives, making it adaptive and personalizable autonomously depending on the received inputs, opens to many chances. Especially for the elderly, being autonomous in daily habits, feeling independent, and not a burden for the family, keeping the health status constantly monitored and postponing hospitalization, are all elements that can significantly improve the quality of life of that category of people.

Considering the current pandemic, something has changed in the way people perceive their own home that has become a sort of safe haven in which to shelter to escape the virus, but at the same time even a prison where you were obliged to stay during the worst phase. That new condition makes necessary a strong improvement of the activities that the elderly should carry out while staying inside the house, avoiding where possible to expose themselves to the risk of infection by leaving the house or attending other people. In the light of this context, AAL takes huge importance as a tool to protect the person by letting him stay at home but without any decrease in the services offered and the degree of protection.

4 Smart Clothing for Elderly

Smart clothing is becoming an essential tool in Ambient Assisted Living for monitoring elderly at home in an ecological approach and in a non-intrusive way, Fig. 2.

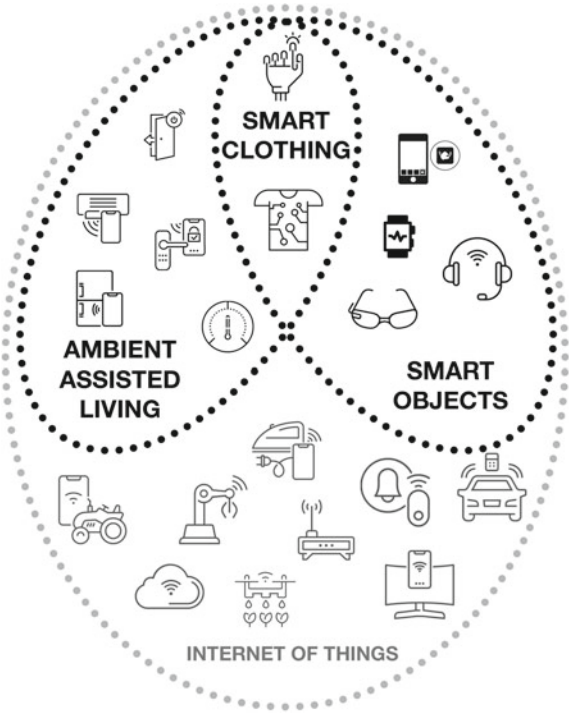

Fig. 2 There is an intersection between ambient assisted living and smart objects, generating the field of Smart Clothing

Smart clothing as other IoT-based device can be used in different scenarios such as in industry, for Defense and Public safety (military), for Ambient Assisted Living in cities and home but also as a tool for personalized care.

Especially, they can be used for monitoring biosignal (physical, biochemical, and physiological), daily life activity, and localization in vulnerable group such as elderly as represented in Fig. 3.

We can distinguish "active," "passive" and "very smart" garments [12]. Passive smart clothing can only sense the environment; active can sense and react to external stimuli and finally "very smart" where they can sense, interact, and adapt to environment and stimuli [12]. According to Rantanen and Hännikäinen (2005) [13], the human system integration is made by different layers. An inner one is between the human and the textile. Moreover, an outside layer is between the garment and the environment. Between these layers, the communication is made by interface as a fastener that serves to support the process unit such as an electronic board that contains battery and IMU sensors for physical monitoring. Between these layers, the communication is spatial, external, and internal. Human system integration and interaction are affected by the wearability of the user. Gemperle (1998) defined the guidelines for wearability composed by 13 items [14]. Between them, body placement, form language (body shape), and accessibility are the main items that should be more considered in designing smart clothing for elderly care. Cho 2009 [12]

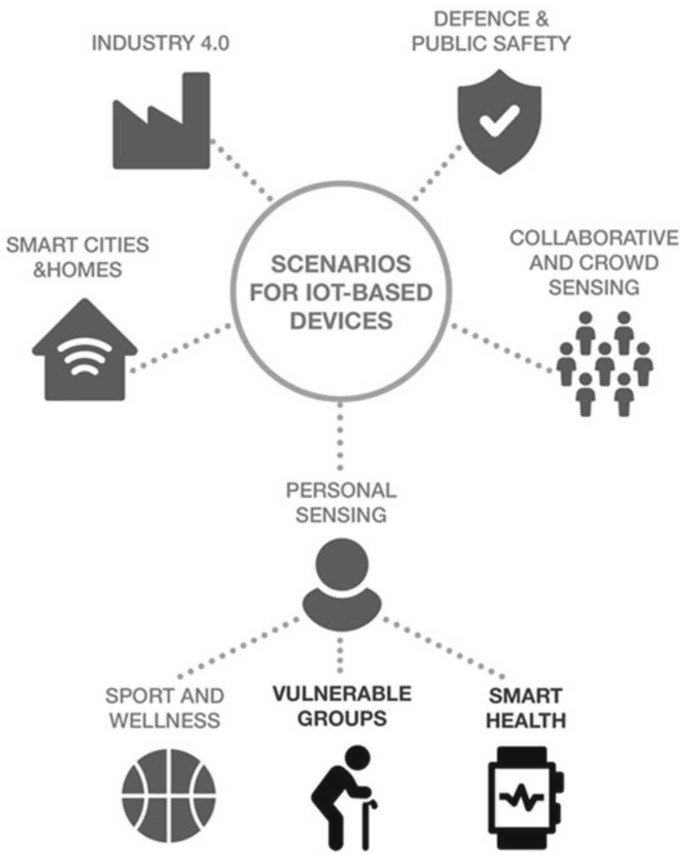

Fig. 3 Scenarios for IoT-based devices

describes body position sensors for biosignal monitoring such as physical (movement) and physiological (electrodermal, electromyographic, electroencephalogram activity, impedance, respiration, body temperature, blood pressure, pulse, blood gas) (Fig. 4).

Furthermore, some of these signals can be integrated into a smart garment for monitoring elderly health and well-being.

An example textrode made of conductive fabric positioned at the chest level is used for electrocardiogram (ECG) and heart rate monitoring by transthoracic electrical bioimpedance measurements [15–17] captured by two fasteners connected in the front with the process unit that contains also IMU sensors or accelerometer for activity detection such as body posture (sitting, laying down,…) or falling. This is connected to a server that communicates by Bluetooth to a dedicated app that allows monitoring of the data in real time or storage of them for successive analysis. This information can be provided to the cardiologist for remote cardiac monitoring (Fig. 5).

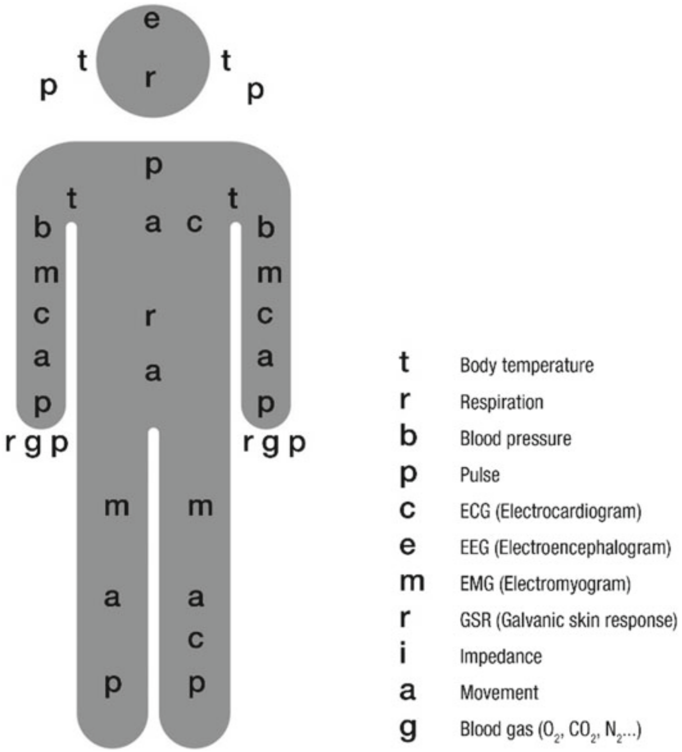

Fig. 4 Biomedical signal that can be monitoring on human body

Besides, Guan et al. 2017 [18] proposed a system that integrates the smart clothing with a home gateway and home server for remote patient ECG monitoring. The device proposed is a smart shirt that contains three lead ECG monitoring and three-axis accelerometer for body states as walking and falling.

The signals are sent from the smart cloth to the home gateway by Bluetooth (low energy). Then, after processing and compression, these signals are sent to a healthcare server developed on the WAMP platform and are transplanted onto the Ali Cloud platform. Elderly can scan a QR code present on the smart cloth through a camera to connect themselves with the home gateway. Successively after login, four different modules such as monitoring center, health records, connection, and system setting appeared, as figure [18]. A similar device is proposed by Huang et al. 2019 in Fig. 4 [19]. Data is collected through the smart shirt and the body tag and a smartwatch. Successively, data is updated to the service that in the case the signal is abnormal send an emergency message to an app to inform the caregiver. Lin et al. (2018) [20] proposed a similar system where the smart shirt is connected by Bluetooth to a network that is connected to the cloud where the data is presented in Web mode to the mobile device of the caregiver or the doctor. The smart clothing device operates

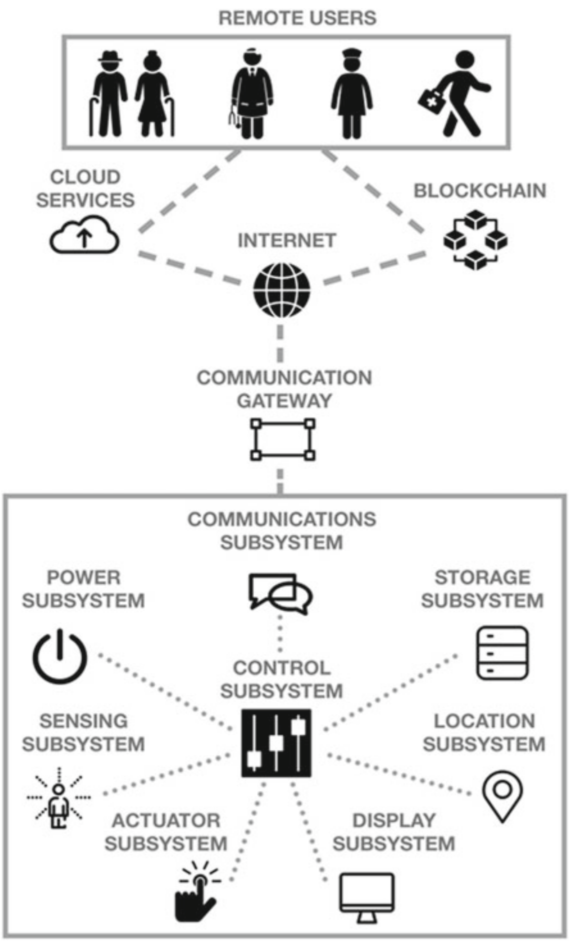

Fig. 5 Architecture of an IoT smart garment system

for surveillance (indoor localization “anti-lost,” tracking physical and physiological status and fall detection).

As MagicIC shirt presents a similar network, the smart shirt is used for home monitoring of cardiac subjects. The smart shirt is connected to a telecommunication system (UMTS) dongle for data transmission to cardiologists. Every patient normally performs three sessions of 3 min telemonitoring for 30 days [21, 22].

Lu et al. 2018 [23] presented a similar network using a smart shirt front zipper with a pocket with a sewn electrode. The proposed system is used for physiological function training, activity domain monitoring, fall detection, and emergency help.

As an alternative to the smart shirt, Burns et al. [24] proposed a bra for monitoring ECG and activity of older walkers through the city. Yeung et al. [25] proposed smart socks for monitoring step count, cadence, and velocity in older and neurological patients as Parkinsonian. As a while, Najafi et al. [26] proposed smart socks for monitoring plantar temperature and pressure and joint angle in patients with diabetic peripheral neuropathy.

Kim et al. 2012 proposed a smart glove for hypertension composed of an inner and outside glove [27, 28]. The inner one contains electrodes stimulating sites for Transcutaneous Electrical Nerve Stimulation (TENS), while the outside protects the inner part. The transmission bands are connected then with an arm band with the tens. The gloves were applied on 12 patients demonstrating a reduction of blood pressure from 142.58 ± 9.90/82.46 ± 4.45 mmHg to 119.83 ± 9.23/75.79 ± 4.90 mmHg in systolic blood pressure.

Likewise, Yang et al. 2018 [29] proposed an e-sleeve for FEM simulation, training software and Kinect sensor testing them in eight stroke survivors.

5 Smart Clothing Acceptance

Smart clothing presents the capability to monitor elderly through the city without affecting their performances, improving assistance and their family caregiving [30–39]. Tsai et al. (2020) [31] proposed a technology acceptance model for investigating 50 elderly perceptions regarding the use of a smart vest for monitoring posture (Fig. 5). Several variables with different items were investigated as shown in Table 1.

Material resulted in one of the most problematic issues affecting the user. In fact, they prefer cotton fabric ant-allergic comfortable and breathable. These conditions revealed an issue that reduced their anxiety.

6 Discussion

Design, aesthetics, and technological issues need to be considered in the functional co-design process for designing smart clothing for elderly. Our suggestion is to use a washable smart garment with breathable fabric with seamless technology. The smart garments need to present front or lateral zip (with easy-grasp pull) easy to dress also if you are sitting or lying down. The smart garment should present a fastener in the front for connecting the cloth with the process unit that can be removed during wash. Besides, these clothes should be connected using QR code or beacon to a dedicated app for remote patients care and monitoring. We suggest avoiding smart bra or shirt that is needed to pull them over the head. In addition, a fall protection pad should be entered in removable hidden pockets. Also, anthropometry and 3D body shape analysis should be considered for designing personalized cloth for elderly monitoring [17].

Table 1 Technology acceptance model as described by Tsai-Hsuan Tsai et al. [31]

Variable	Items	Description
Technology anxiety	TA1	I feel apprehensive about using the smart clothing system
	TA2	I hesitate to use technology for fear of making mistakes that I cannot correct
	TA3	I am afraid that the equipment may suddenly stop functioning
	TA4	I do not want other people to see me wearing smart clothes
Perceived ubiquity	PB1	A smart clothing system that provides healthcare information "anytime and anywhere is crucial
	PB2	The smart clothing system provides me with anytime and anywhere communication and connectivity
	PB3	I will use the smart clothing system very often for health purposes
Resistance to change	RC1	I do not want the smart clothing system to change the way I deal with related problems
	RC2	I do not want the smart system clothing system to change the way I keep myself healthy
	RC3	I do not want the smart system clothing system to change the way I interact with other people
	RC4	Overall, I do not want smart clothing to change the way I currently live
Perceived usefulness	PU1	Using smart clothes will improve my life quality
	PU2	Using the smart clothing system will make my life more convenient.
	PU3	Using the smart clothing system will make me more effective in my life
	PU4	Overall, I find the smart clothing system to be useful in my life
Perceived ease of use	PEOU1	I find the smart clothing system to be clear and understable
	PEOU2	I find that the smart clothing system does not require a lot of mental effort
	PEOU3	I find the smart clothing system to be easy to use
Attitude	AT1	I think that using the smart clothing system is a good idea
	AT2	I think that using the smart clothing system is beneficial to me
	AT3	I have a positive perception of using the smart clothing system
Behavioral intention	BI1	I intend to use the smart clothing system in the future
	BI2	I will always try to use the smart clothing system in my daily life

7 Conclusions

Coronavirus (COVID-19) pandemic is changing many aspects of our lives: we are experimenting new daily habits, new ways of interacting with other people, a new perception of the environment, and a new relationship with our home spaces and objects. Considering this unexpected modified context, it is important to protect the most fragile categories of users as the older people, who were the most severely affected by the virus. Human-Centered Design smart clothing in Ambient Assisted Living revealed to be a promising IoT device for monitoring elderly health care and well-being in a society that is becoming more a smarter eliminating borders enhancing a new vision of quality life and care. Several smart garments already exist in our society. But some of them are not responding to the requirements of device fit for the purpose of the elderly user's care. Our suggestion is to use HCD approach for design smart device that is washable, easy to wear, and comfortable without limiting elderly user movement enhancing and improving life quality, lifestyle, and health. In the next future, it is necessary to research and invest more energy in this domain for improving the health and welfare where humans are the protagonist. By 2030, we will have more elderly than youngers, and aging will affect more and more human being of a smarter society. Future perspective needs to be addressed to empowering Ambient Assisted Living where Human-Centered Desing smart clothing will become an essential tool for protecting senior citizens.

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Implicit Intention Communication for Activities of Daily Living of Elder/Disabled People to Improve Well-Being

B. G. D. A. Madhusanka and Sureswaran Ramadass

1 Introduction

The elderly is now seeing a significant increase worldwide. More than 11.5% of the world's people are aged 65 and older in 2012, and by 2050, it is predicted to hit 2 billion [1]. The problem raised by these figures is the care of the people who prefer to save their independent lifestyles, often at high risk. Also, extra care homes are commonly used to provide protection, reassurance, and health support for the elderly living in these facilities. Within such an environment, older people feel more comfortable conducting their day-to-day tasks while a dedicated team offers 24/7 emergency care services [2].

In recent years, the growing number of older people, especially those living alone away from their families, has become a severe problem. Although it is essential to look after them, it has become difficult, and a family burden. Dangerous situations often occur because of this problem, including life-threatening ones. The caregiving concept has merged many ways, such as based on the independence of their activities of daily living (ADL) for both elderly and disabled people [3]. A caregiver's most important aspect is to understand the intentions of the older person, with the minimum number of interactions. This research aims to establish a novel technique for understanding a human's implicit intent by using non-verbal communication in conjunction with computer vision technologies. After identifying the older person's

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_16

implicit purpose, the program defines the appropriate activities/requirements relevant to the home environment. The novel technique will help the elder point them out with the eye-gaze movement to fulfill the user's visual attention by his intention. Then, the implied intention can be used to forward proper service to the caregiver [4].

The implementation scenario of this implicit purpose contact on ADL for older people involves a home care environment with a caregiver, where a person with a physical disability and even a total lack of speaking capacity has to request a caregiver for a user on ADL [5]. The caregiver is in the home setting at different locations and feeds the disabled individual live scene pictures or videos back. In the home setting, the focus of the impaired person on the scene picture is monitored and interpreted to infer the intention of the impaired person. A disabled person's stated purpose is forwarded to the caregiver for proper support [6]. The main goals of this research are the implicit recognition of intent in which movement of eye gaze is analyzed to infer the intention of the user in ADL and visual attention system.

Recently, the implicit goal of exploring the usage of specific markers has started to draw the attention of researchers. Gaze outcomes are related to a variety of cognitive processes such as allowing a source of knowledge about the purpose of a person to be seen implicitly [7]. Even the intentions of people are challenging to use their eyes. The vision of the eye is an intelligent system not designed for engine operation. The eye will never disrupt the usual vision function of the elderly affected. Deduce the interest, and the eye may reflect the concentration of the brain signal on the elders affected [8]. It is not yet clear whether visual attention is related to human intention.

The implementation scenario in this eye-based purpose contact system involves a home setting with a caregiver where an individual with a disability who is restricted to a bed or chair will replicate the input scene picture provided to a person with a disability to conduct an ADL. The pictures of the incident move to various places in the home setting, and the input lives the photographs of the wounded victim. And his vision of the scene picture is monitored and evaluated to infer the purpose of the affected individual. The verified purpose is then transmitted as action orders to the caregiver. This frame comprises several key components: detection of visual attention with detection of visual objects, knowledge of social purpose and intention.

At the point when a user eyes focused on the object, sensory interest may be represented as a cluster of perspectives. Detect visual attention and develop a visual behavior-based classification to distinguish a visual attention pattern from natural visual behavior. The use of the eye to intentionally infer visual attention requires a distinction between regular behavioral movements of the eye. Ensure visual focus, and additional detail is often required. The standard arrangement is to ask an inadequate user to flicker his eyes to confirm visual attention intentionally. A new method which can indirectly identify visual focus is vital to minimize a person's cautious effort.

The focus of the authors' research is an implicit intention communication for elderly people on daily living activities of elder people who are in deaf and disable. Elder's eye-gaze movements are tracked and analyzed to infer the user's intention in ADL. A questionnaire based on context features is used for the intention recognition system. This chapter studies the feasibility of using eye-gaze tracking to address those research issues.

The rest of this chapter is organized as follows. Section 2 presents an approach to implicit intention understanding with eye-gaze communication. Section 3 describes recognizing activities of daily living to improve well-being. Section 4 contains emerging challenges of eye-gaze tracking and implicit intention communication. Section 5 describes methodology and Sect. 6 presents experimental setup. Finally, Sect. 7 presents the most relevant conclusions of the chapter.

2 Approach to Implicit Intention Understanding with Eye-Gaze Communication

Human mobility is impaired and even severely lost due to aging and critical injuries or illnesses such as spinal trauma, paralysis, stroke, amputation, and Parkinson's disease [9]. These diseases would be challenging or unlikely for these individuals to conduct standard ADL separately. Daily activities include standing, dressing, cooking, eating, and more. Assistant technology, including assistance aids, interactive handmade tools, expects that the autonomous everyday lives of aged and impaired persons can be enhanced. The obstacle to the adoption of assistive technologies will be significantly minimized between individual users and assisting robots [10]. The limitation is the absence of sufficient correspondence to allow the elder and disable people to communicate successfully and generally with the assistance framework. This issue can handle using devices with higher practical limits become increasingly viable with higher functional capacities to become more and more effective. Today, the user must generate explicit requests for service to control the support system, mainly involving large motor movements. Communications modes include speech, joystick, gesture, physical contact, and electromyography.

All the above modes of communication require multiple muscles which are strong enough to cooperate. They are still not accessible for older persons with restricted mobility. A brain-based connectivity system is another essential experience. However, it is all in its early stages. To accomplish viable advancement toward the common human–machine association, new advances that are anything but difficult to utilize and reasonable for individuals with low versatility limit are essential [11]. Gaze movement requires minimum effort to human beings, and most elderly and disabled people can still control their eyes. Eye view is indeed a positive way to communicate with the aged and injured care group. Gaze tracking is a technique which continually assesses where distinctive looks (looks) in real-time are based on observational eye disability. As regards the hardware for motion control, three types may be classified: contact lens, EOG, and optical process [12].

The optical process is based on a video camera capturing an image of the eye. Optical techniques are non-invasive and cost-effective. Eye gas capture as an optical process is used in psychological/mental studies, the interaction between humans and computers (HCI) and the interaction between humans and robots (HRI) [13]. For HCI, the interface is typically used to choose buttons or text in the on-screen application keyboard as a pointing tool. The HRI uses the gaze remains to indicate the direction of the robot to the approaching location or object.

The thought of increasing human capabilities through wearable techniques has engaged people's minds for a long time. Starting with the creation of eyeglasses and pocket watches to enhance vision and keep track of time; developing the concept of attaching "artificial devices" to human organs to stimulate senses [14], such as hearing and touch. Nowadays, with the enormous development of digital technology, along with the expansion and shrinking size of computers, wearable technology seeks to blend computers and sensors with the human body, to facilitate communication between individuals and the digital content they wear. Technology has thus been integrated into clothing, jewelry, and accessories, e.g., watches and eyeglasses, and all other items that humans can wear, to simplify their everyday lives and give them pleasure and luxury [15]. Modern, flexible display techniques, electronic textiles, and physical computing provide an opportunity to consider combining these technologies to offer their users a tool for interacting with digital information in ADL [16].

Wearable technology can play an essential and primary role in caring for older people, making their ADL easier. These devices can help them take care of themselves and promote their independence [17]. Sensors and tracking devices can be used to remotely observe the vital functions of monitoring their health and sending messages in the event of an emergency. The drawback of wearable technology is that when people grow older, their critical services, physical and mental abilities decrease, and they face difficulties in using and interacting with advanced technology [18]. On the one hand, older adults need individual devices and applications that can help facilitate their lives and daily activities and, at the same time, consider their physical and mental needs and capabilities. On the other hand, many specialized wearables have a mechanical or medical appearance, which may cause them to feel embarrassed, helpless and self-care, which may discourage them from using these wearables [19]. However, older people who are deaf and disabled but retain visual capabilities have not been helped to use wearable technologies.

3 Recognizing Activities of Daily Living to Improve Well-Being

ADL refer to regular tasks that an individual may conduct without external assistance. They are typically divided into six groups: food, bathing, dressing, toileting, transfer, and continence. In the assessment of their health condition and need for long-term care, people can continue to conduct ADL. Older people also suffer from physical or cognitive impairments at various levels at which ADL output tends to decline with age [20].

For example, government-subsidized workers in supported residential facilities that, through the law, be mandated to collect residential ADL data 24/7, particularly for those afflicted through mentally disabled diseases such as Alzheimer's. Relevant areas, including roaming, crashing, sleep consistency, or memory lapses, drew researcher's interest [21]. Present off-shelf monitoring software on mobile health products (smart time machines, smartphones, and exercise trackers), owing to restricted availability, does not calculate their ability for working with complicated ADL. Most industry trackers record only primary health details such as calories consumed when activity was taken by miles walking or running on the treadmill, and then, heart rate is achieved [22].

Studies have suggested proposals such as the deployment of multiple conventional sensors for identification in a connected home setting [20]. Examples include door contacts, infrasound sensors, sensors for lamp switches, and almost perfect microphones. Many devices utilize sophisticated methods for tracking video signals using either a traditional camera or Kinect. Due to the grave concern about privacy, however, vision-based monitoring systems tend to lose the user's trust.

Even all the advances and tests, the usual non-portable costs for sensing and monitoring equipment for deployment and maintenance remain high. The networks of the body sensor which use sensors like the chest, finger, and waist nodes to increase the capability of the sensor are a remarkable step forward. Consumers will, however, be equipped with buttons. Recently, scientists have proposed to enhance the current medicine by adding a medicalized device to online medical substances [21]. Functionality, cost, and convenience are driving forces for business and are crucial to consumer value and smart living conditions. We are launching an ADL recognition program, defined as the open single-point mobile application for smartphones, to provide anyone wishing to achieve improved user experience in an inexpensive way of living.

3.1 The ADL Recognition System

The development of smart ambient systems contributes to significant technical developments, including embedded technology [23]. Various forms of sensors and actuators have been used to communicate with their users to enhance, track, or encourage everyday operations. Such technologies have been employed in numerous real-world contexts throughout the past two decades, and these include private and public settings, including schools, colleges, libraries, homes, and enterprises [24]. Recent census studies have shown that the number of older people is increasing sharply, relative to the rise of all other ages [25]. This finding poses than the issue whether society should help this elderly demographic, typically suffering from recurrent or advanced diseases (such as hypertension, Alzheimer's, and diabetes), by sustaining or supporting their wellbeing and well-being [20].

Automatic physical activity recognition has emerged as a critical area of mobile and omnipresent computing research. For the supporting life, health monitoring, fall detection, and the old network of help, sensor-based behavior recognition is critical. For over a decade, vision-based solutions to behavior recognition have become widely established, but success is not enough. Most approaches deal with different phase forms, but nothing is done to identify the excellent and vital behavior of older people, including the identification of fall [20]. A person may fall and suffer injuries which restrict mobility or events that can lead to health deterioration. The detection of changing trends can be of great benefit to decision-makers or emergency diagnostics caregivers, particularly in conventional monitoring systems [26]. Recognition of sensor behavior is a crucial part of several applications, especially for the elderly in care centers, and intelligent homes. The detection of events deteriorates because, owing to several factors, incomplete data is missing. Therefore, this work recommends a method to improve the identification of events with missing data used by the LoRaWAN sensors [27]. In total, 42 LoRaWAN sensors were also used for the analysis of data loss performance at a healthcare center in Japan. This work has also established a large dataset of the everyday lives of older people from different devices, including input from nurses on the planet. In this data collection, they discussed various behaviors of older citizens. They concentrated on working on grasping activity measurements, positions, and sleep cycles through insightful technologies and algorithms for machine learning.

In various premises of the caregivers, an improvement in the consideration for new consideration homes, an observing framework comprising of various types of non-obtrusive sensors was introduced [28]. This research was not intended to track older people dealing with diabetes or health issues but was mostly used to obtain data on their ADL. Older volunteers, for example, face conditions like hearing loss, impaired vision (i.e., partial loss of vision), physical impairment, diabetes, etc. The difference between medical conditions will influence how someone conducts ADL as expected, and irregular activity in each situation that prevents their identification can be described differently. In the context of interventions in various parts of the home with additional treatment, the detection of unnecessary actions/comfortability that can influence the well-being of the elderly was observed. The following ADL are personal grooming and toilet, preparation of breakfast, lunch, evening meal, and sleep.

It is important that ADL such as multiple or similar incidents occur on a typical day. The Canary Care [29] non-intrusive sensing device is used for the collection of details needed to monitor the operations. A lock, orientation, temperature, and light sensor are included in the device. Moreover, houses are equipped with non-intrusive sensors such as grid eyes and power sensors, which are used to find occupants in rooms and recognize electrical appliances. It is important to note that the integration of the ADL is carried out through the evaluation and modeling of the data obtained by all different sensors using Petri Nets. Duration, distraction, and time of day [30] are criteria for the proposed ADL-unification method.

Another non-intrusive monitoring system for aging populations was suggested by the project ProSAFE [31]. This device comprises a series of infrared motion sensors mounted in different rooms of the smart building. The spectrum of this project has developed a predictive model that can sufficiently identify suspicious activity while conducting ADL [32]. Instead, a highly daunting sensor network composed of several sensor types that can be used in residential areas to detect the everyday movements of individuals is recommended in the SPHERE proposal. A mixture of sensors, including video monitoring modules (such as security cameras), compact sensors (such as wear movement sensors), and environmental sensors (such as doors, orientation sensors, illumination, temperature, vibration, and power sensors), is related to individually [33]. All these sensors are used to collect normal or abnormal behavioral detection data in these smart home environments during daily activities.

Plan and create reliable, keen structures that can genuinely screen the everyday exercises of users, a far-reaching comprehension of their working is required. Accordingly, the detecting structures and action acknowledgement techniques utilized in these conditions have pulled in the best consideration. Sensing devices installed in the circumstances like smart homes typically require a mixture of sensors that can sense activity, temperature, illumination, water intake, and other environmental variables that may help to identify ADL [34] reliably.

Also, providing various, efficient embedded instruments, such as accelerometers, temperature sensors, and gyroscopes, smartphones today [35]. The detecting of human body developments by utilizing smartphones is one of the latest and testing applications for both fall identification and activity recognition. An alternative to the problem is the use of smartphones with sensors. As a consequence, research has been suggested over the last few years to consider human activity with smartphones: for example, over [25] and one of the first solutions to the usage of an Android device for ADL detection utilizing its built-in accelerometers. There have already been detailed academic findings [29]. Improving the ADL classification efficiency through standardization of performance appraisal measures is planned to proceed in areas like multi-sensor fusion [36].

A variety of simulators also assist in the testing of ADL study methods. Some of these simulators simulate move or sensor measurement over time with the current ADL sequences [37]. Simulators depend upon established data sets, either through the capture of ADL sequences from real, online accessible individuals or through manual building loops. A certain amount of effort is required to build datasets manually, and the identification of ADL sequences from the actual world involves only real-life actions. These simulators cannot be used to test ADL monitoring tools for predicting long-term behavioral shifts. Over several months or years and activity that happens periodically in the physical world that cannot be documented in the data collection of a specific individual. Moreover, in these test systems, practices for specific likely dangers or inconsistencies cannot be presented. To order to test this software [38], ADL Simulators help to ensure that the long-lasting ADL datasets are generated safely and automated.

The advent of assistive robotics gives the ability to regain critical independence rates for the aged and the disabled in ADL. The existence of a way to render HRI both functional and intuitive is, therefore, one of the critical challenges. Although people may communicate their expectations in several forms (e.g., body actions or expressions, voice or expression patterns), the transmission of tacit intention on the face is still underdeveloped. Li et al. suggested in 2017 the development for HRI of a modern non-verbal tacit eyeglass contact framework [39]. In this situation, user eye-vision gestures are proactively controlled and evaluated to deduce the user ‘s goal in ADL. The supposed purpose will then be used to guide assistant robots for proper operation. The benefit of this system is that most people can utilize gaze-based contact because it needs less effort, so most aged so disabled individuals will maintain their visual ability. It is expected that this framework will simplify HRI and improve the adoption of technology support and user independence in everyday life. This method was first established for a more in-depth interpretation of the interaction between sensory activity and the mental mechanism in the intentional human language.

The integration of visual communication into useful, practical, and intuitive human-machine interaction remains a question. This research enables the elderly and the disabled to make their requests for services naturally, intuitively, and without effort and with minimal mobility. This work has not impeded a balanced visual activity of the individual but allows a variety of nuanced expectations to be articulated. The simplification of Human-Machine Interface (HMI) is expected, enhancing the use of assistive technology and the independence of the user in everyday life and quality of life [39].

4 Emerging Challenges of Eye-Gaze Tracking and Implicit Intention Communication

The contribution of this research is identified in three emerging challenges respective eye-gaze tracking and implicit intention communication.

1. Natural user interaction.
2. Head pose invariant gaze estimation.
3. Implicit intention communication for older people who are deaf and disable but retain visual capability on ADL tasks.

4.1 Natural User Interaction

Throughout recent years, the critical work focus has been to track the position of the consumer seated on the computer. In recent years, however, an increasing range of indoor and outdoor displays [40] have been introduced, including kitchens, living areas and parks, providing excellent incentives for consumers to connect and interact [41]. Because eyewitnesses instinctively and for a limited period engage with the show, the complexities of monitoring multiple items are nearby. The program had trouble detecting the exact item sought by the user and recognizing user behavior while the user was searching for items intentionally [42]. Tools that tackle this problem seem to be gaining momentum in the literature [40], which contribute to daunting implementations for environmental outdoor and indoor gauze tracking.

4.2 Head Pose Invariant Gaze Estimation

The ability to infer the orientation of the human head from the image details called a head pose estimate through a globally organized context poses an inherent challenge which created considerable interest in the computer vision community [43]. Nevertheless, the application of gaze projections based on eye rotation measurements alone [44], with details regarding the head position, enables the gaze prediction in the different eye and head positions to be measured. The assessment of the look is especially important when observing the expression of the eye in which determining the head position reduces the constraints on the normal movement of the user's eyes. By utilizing defined head posture constraints [45], chinrest [46], or portable setups frequently resist the need for head position estimation but are incapable of tracking the eye view remotely [47]. The history of consumer contact with public shows, particularly the absence of allowance for head adjustment, limits the individual to an unnaturally set head posture that is challenging to sustain, which sometimes contributes to inaccuracy or loss in breach of this condition [48].

4.3 Implicit Intention Communication for Older People Who are Deaf and Disable

Hearing deficits have significant detrimental impacts in all developmental fields, including vocabulary, neurological, psychological, emotional, and behavioral function. As a result of this potentially delayed development, people who are deaf or hard to hear are at higher risk of psychological wellness issues in comparison with their typically developing peer problems. Scholars who assess cognitive and behavioral disorders in people have focused on home mates' questionnaires [49]. The growing number of older people, especially those living alone and apart from the rest of their families, has also become a severe problem. Monitoring these people is compelling but challenging, and a burden on their families. Deaf people have identified significant challenges in communicating with caregivers, as communication barriers in life are linked to poor physical and mental health. Also, society is getting complicated, and it is because of the need to pay high salaries for caregivers. Moreover, a shortage of caregivers will become a severe problem in the future. To prevent this, the implicit intention of a human user is recognized as a novel method. Non-verbal communication is used to identify the user's intention to identify the activities/requirements needed from the home environment that will help the elder with eye-gaze movement to point out that user intends to do so [50]. This concept is expected to work with older people with disabilities to raise their living standards.

5 Methodology

Since the early 1950s, ADL has become more widely accepted as an elderly and disabled caregiver. Throughout the industrial and academic laboratories, tremendous development has been achieved throughout ADL [51]. While these support solutions give elderly and disabled people the promise of independent everyday lives, the biggest challenge is the lack of sufficient connectivity to allow older people and disabled people to communicate efficiently and intuitively with these supporting devices. This impediment between citizens and the smart home idea of ADL could considerably hinder the adoption of such supporting technologies. Types of human speech involve expression, joystick, gesture, physical contact, and EMG. Users will, therefore, create clear/implied service requests and use them for new engine motions. The introduction of higher-level assistance services would worsen the problem. Make tacit and modern, quickly understood, and convenient and realistic methods that consumers with limited action or non-verbal capabilities can use.

Ideally, the HMI would be able to proactively, indirectly, and immediately consider the user's wishes when delivering required services. Appropriate funding should also be based on adequate, accurate, and original technology of inference. To deduce a user's intention in HRI, researchers have studied different behaviors, such as motion/style, language/speech, and EEG [52]. A missing eye is another natural symbol which can be used to understand the intent of an ADL human.

Studies indicate that sensory perception is closely correlated with executive human processes. Once an entity focuses physically on an object, it is perceived by the person, and the attention period is directly connected to cognitive processes. The literature has shown that shifts in visual behavior can alter human mental states [39]. Things depend on disclosing a person's unique wishes. For example, if someone was hungry and needs some water, then they appear like drinking items spontaneously and intentionally, such as a water pump, a cup, or a water bottle. This innate and clear connection with the purpose of the eye is a positive sign of consciousness. Gaze management also requires little user effort. Gaze contains positioning details for the orientation of a visual object and offers vital place information for robotics working. The gain is shown by the fact that multiple apps operate in complex ADL.

5.1 Attention-Based Object Recognition

A cluster of perspectives on the object can express visual attention when a person's eyes focus on an object. Visual attention recognition and analysis of visual activity were established to differentiate a pattern of visual focus from normal visual speech. This feel style is named "intentional vision," which indicates that the consumer uses the visual target to tackle it. Around the same moment, as you search or investigate, these are calling the "intentional free gaze," gazing at an entity without the function of a manipulator. Unlike the traditional long-term and conscious blink, the monitoring

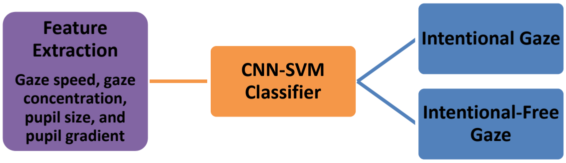

Fig. 1 Detection of intentional gaze using a CNN-SVM classifier

of attention using a normal visual behavior does not allow users to acquire and recall specific instructions or perform artificial rituals, which minimizes user knowledge. A hybrid model [53] of CNN-SVM is then implemented for the visualization, and an analog circle for the display of the visualization cluster is established. Furthermore, items visualized will be observed and identified in the field of human focus overlaps with the background of the scene.

The visual behavior recognition classification is based on the CNN-SVM and is shown in Fig. 1. This classification uses visual characteristics derived from a natural visualization, which do not require users to exercise unnatural visual actions, such as an extended look or a deliberate blink. The parameters for this category include the time of the look, variation in pupil size/gradient, measurement intensity, and measurement concentration. Such characteristics have been picked based on laboratory evaluation and the literature review [54]. The classifier is qualified to differentiate the award from the inactive. The generated eye-blind characteristics are incorporated into the classifier, and the result is the best indicator of the user's role in the specification. It is only when a deliberate focus is observed that the eye is attracted. The derived visual characteristics are entered, and the output is the latest approximation of the user's view status.

5.2 *Human Intention Inference*

The approach to infer the purpose of the user may be that the user directly expresses the desired target by, for example, non-verbal instructions. However, the need for implicit user communication may lead to active cooperation. Individuals also learn how to anticipate certain people's expectations through experience and prove that objectives can be extracted through non-verbal communication. This research examines how non-verbal gestures and indirect signs indirectly provided by the recipient may be utilized through the implicit intention of the touch with older people to render smoother and more normal communications simpler.

This work suggested commands for user control, including elderly eye-vision gestures, and examined to extract the user's purpose from ADL. The proposed method of this research is the CNN-SVM model for informing the recognition of human intentions. The study aims to evaluate the inferred intention, and any assessment is usually conducted only in domestic scenarios. For the intention recognition system,

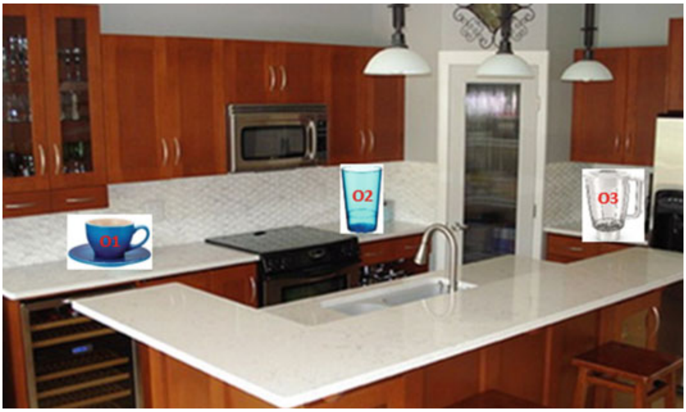

Fig. 2 Artificial kitchen image with labeled objects

a context-based questionnaire is used. Later, caregivers should make decisions or diagnose situations based on the intention recognition system.

A new method is applied in this study to recognize a human user's implicit intention by using a non-verbal communication combination with computer vision technology. After understanding the user's implicit intention, the system can identify indoor activities/requirements necessary to help the older person to point the eye to his/her intention. The goal is instead based on appropriate service providers. A joint CNN-SVM model was proposed in this research to use the context-based questionnaire process to the system for the intentional recognition, which improved the accuracy of the classification and the overall capacity of the CNN classification using the SVM combination.

Experimentally identified three objects of intent in the image of the kitchen. The intention knowledge is developed with the three objectives "'cup" (O1), "glass" (O2), and "blender jar" (O3). All the manipulator objects have been included in the picture of the artificial kitchen. The analysis is centered on sensory perception and purpose, which are essential components of the entire household scenario. The local scenario is based on the user's input scene, as seen in Fig. 2.

5.3 *Gaze-Based Implicit Intention Communication Framework*

As shown in Fig. 3 describes the gaze-based implicit intention communication framework the modules are combined to shape the whole the user looks at the live scene in which the HMI supplies the kitchen. The HMI is expected to hold a stable image of a scene containing objects for the user during the intentional expression process. By pressing the switch, the user activating the aim deduction engine begins to examine

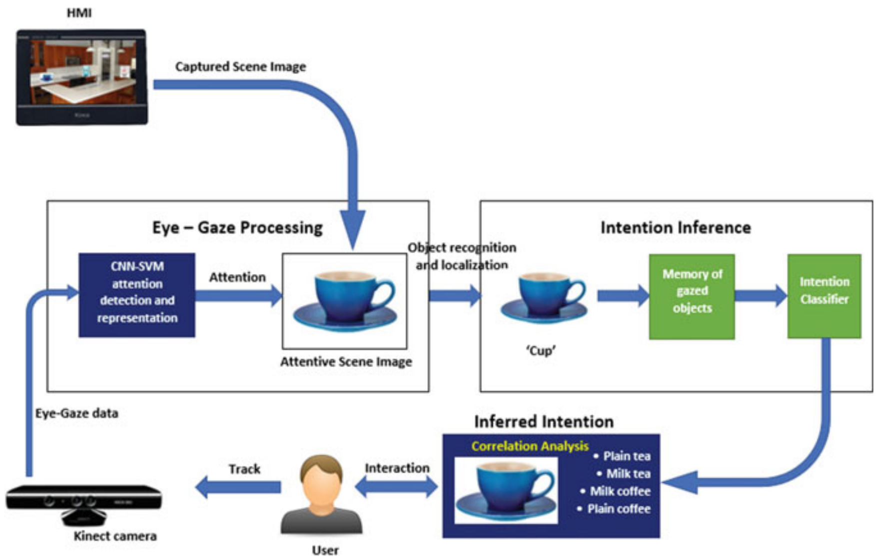

Fig. 3 Gaze-based implicit intention communication framework

the visual gazing data to determine the items stared at and inform the user of the purpose. The result inferred shall be submitted to the user for confirmation on the monitor.

6 Experiment Setup

The experiment concentrates on the detection of visual attention and intention, which are vital components of the overall framework. As seen in Fig. 4, the artificial kitchen setting is replicated by a picture of the user's feedback scene. The scene illustrates a kitchen with visible objects. The NUIA eyeCharm camera is used to track the subjects on the screen. The users sit before a monitor showing a picture of the kitchen scene during the experiment. By looking at such items, users are asked to communicate their purpose to the HMI. Their eye movements and the position of the eye are recorded. The CNN-SVM classifier was used to detect visual attention using eye-gaze data and to detect visualized objects. The user 's purpose is derived from the artifacts shown using the Bayesian Naive Graphic Probabilistic model. Following the experiments, all users will receive a questionnaire to assess their model user experience. The survey includes practicality, user-friendliness, natural learning, and satisfaction.

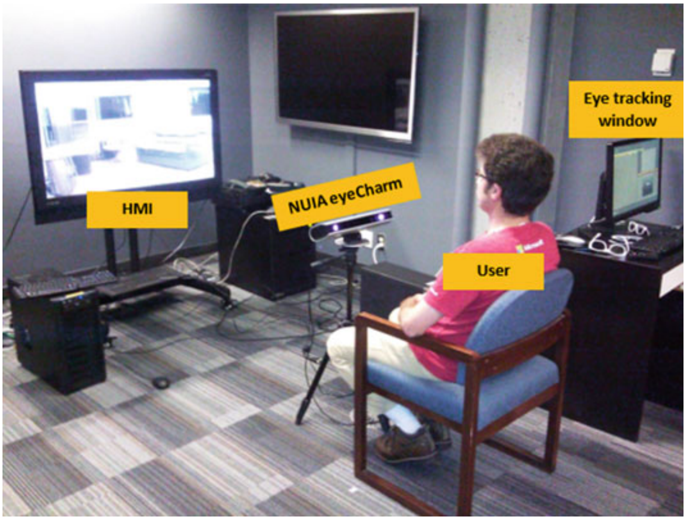

Fig. 4 Experiment setup for gaze-based implicit intention communication

6.1 Implementation of the CNN-SVM Combined Model

The hybrid CNN-SVM method model is used to construct a computer vision tacit purpose dialog model. The SVM classification is done by removing the completely linked layers after the well-trained CNN classifier has been achieved. Since CNN is primarily intended to process the image, it usually arranges feature maps and kernels in square matrices. The implementation process of a hybrid CNN-SVM configuration is shown in Fig. 5 [53].

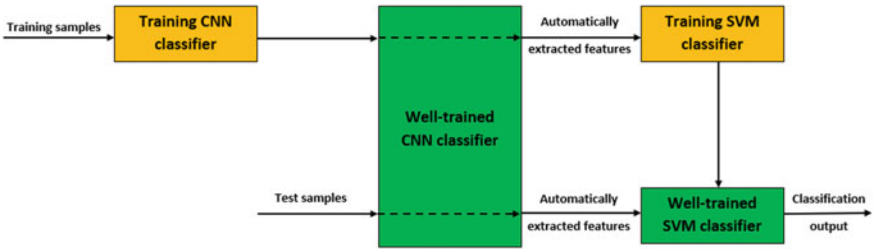

Fig. 5 Implementation process of the CNN-SVM combined model

6.2 Questionnaire for Usability

To assess the user-friendliness, reliability, and user-friendliness of a product or service [55]. In the thirty-part study, four aspects of usability are examined: accessibility, accessibility, learning ease and happiness. For success metrics, individual responses to the usefulness of a device or service appear to be overlooked. Nevertheless, these measures also assess facets of customer interaction and are directly related to consumer behavior and purchasing decisions. The questionnaires are structured as a Likert rating scale of five scales. Users are required to score their satisfaction with the claims, from a deep disagreement to a straightforward comprehension. For assessment of customer perceptions toward a range of consumer goods, different types of questionnaires are used. Users evaluate goods mainly through the usage, quality, happiness, and accessibility in three dimensions.

The users should provide the USE questionnaire utilizing the three accessibilities as mentioned earlier, reliability and ease of use criteria after the gaze-dependent implicit purpose communication system has been developed. In total, 25 participants also took part in the system validation studies. Moreover, they fill out the USE questionnaire and ask users to observe the numbered objects in an artificial kitchen environment. At the point where a particular object is viewed intentionally, a button has been pressed to show the system that visual attention is currently paid to this real object. The display was then automatically updated to focus on the visualized object. Out of this confirmed visual attention are extracted eye look features and used as positive training data. Negative training results with gaze results are reported but are not authenticated.

7 Conclusion

This research presents a method for people who are elderly/disabled to improve their living standards. The behavior of the elderly must be a successful approach to generalization. The deaf people reveal significant challenges in communication with caregivers since communication barriers in life are linked to poor physical and mental health of them. Also, society is getting complex and due to that need to pay high wages for caregivers, difficulty in finding well-trained caregivers, and unlikeliness of caregiving tasks. This study paper aims to promote ADL in deaf and disabled people, to check the proposed structure of engagement with target users, and the next step for the author is to obtain results and validation. The gaze-based implicit intention framework is developed to experiment with each function of the component. Also, the suitability of this type of system for monitoring the activities of the elderly/disabled. The combined process model of CNN-SVM is used to develop an implicit intention communication model using computer vision. The confirmed intention of an impaired person is sent to the caregiver for proper service. The communication to the caregiver and service is not covered in the scope of this research. Future work will be to experiment with the subjective usability of the experimental model in the effectiveness, happiness, and comfort by using of the USE questionnaire.

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A Semantic-Enabled Smart Home for AAL and Continuity of Care

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1 Introduction

This chapter presents the results achieved in the field of the smart home (SH) through the research activities conducted within the Smart and Human-Centred Living Environments (SHCLE) of the Lecco's STIIMA-CNR. Although there is not a univocal definition of SH, one of the most used definition states that it is "a residence equipped with a set of tools aimed at responding and anticipating residents' needs" [1]. Since the early 2000s, it was clear that the SH aimed at enhancing dwellers' comfort, well-being, indoor safety, and entertainment by leveraging the cooperation among the different devices deployed in the domestic environments. The SH is expected to deliver to its target users tailored services, including personalized health care, in order to help them coping with their limitations and to actively support them in performing activities of daily living [2]. Researchers saw in SH technologies a promising answer to the needs raised by Ambient Assisted Living (AAL), a set of disciplines dedicated to develop solutions to elderly and frail segments of the population through ICT

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G. Marques et al. (eds.), *IoT in Healthcare and Ambient Assisted Living*, Studies in Computational Intelligence 933,
https://doi.org/10.1007/978-981-15-9897-5_17

technologies [3]. The aim of AAL is to make the living environments (not limited to the house, but including other social contexts, like workplace, retirement home) “smarter,” by combining sensing technologies, computing, and devices. In this way, AAL solutions, services, and products can help residents to live more independently. As a result, also SH technologies have been designed to address mostly the needs of specific segments of the population, such as elderly and people characterized by motor or cognitive impairments.

SH has become a widely investigated multidisciplinary research field—one that can be faced from many different points of view. From a computer scientist perspective, the role of devices and how these can interact to deliver personalized services covers a pivotal importance, together with SH systems’ architectures [4, 5]; designers and psychologists are interested in understanding the usability and acceptance rate of SH-based technologies among their target users [6, 7]; health researchers are involved in creating and assessing protocols and applications for tailored health-related services, and in evaluating the effects of these solutions on aging populations [8, 9].

One of the most relevant technological paradigms providing the basis for the SH and AAL research is Internet of things (IoT). Since its first appearance in 1999 [10], IoT was considered as an extension of the existing Internet enabling human-to-machine interaction, and in the past 20 years it has been extensively debated as one of the enabling technologies for SH and AAL solutions, particularly in relation to RFID technology, wireless sensor networks, artificial intelligence (AI), and cyber-physical systems. Meantime, in the industrial field, IoT technologies are increasingly used and in particular they are considered one of the enablers of the ongoing Fourth Industrial Revolution [11].

As IoT enhances the connection and interaction of things, it creates the conditions for a seamless data exchange among them. Under these conditions, these devices are therefore endowed with intelligence, network-connected, mostly “invisible” to humans, and they interact with each other to provide services (a situation described as ubiquitous computing [12]), thus becoming the so-called smart objects.

The recent evolution of IoT technology is bringing new technological challenges and new opportunities in the field of SH research. As a consequence, researchers’ attention has shifted to try to respond to new technology-related open challenges. IoT offered researchers the possibility to move from a residence perspective to a city perspective, therefore making the smart city, in which the SH is one of the “bricks” constituting the more complex system, a relevant research field. The challenges and opportunities arising from the concept of SHs (and even from the concept of smart cities) are numerous. Among these, there is energy efficiency, which in IoT-enabled smart environments sees a convergence of interest from AI and energy engineering. In this context, the SH, as part of the smart city, requires the possibility to manage and distribute energy in an intelligent way—both in a single SH and in the entire smart grid—and in this sector, IoT leverages different protocols to foster the adoption of residential, business, and city solutions [13, 14].

A second concern related to SH connectivity in smart cities is machine-to-machine interaction: Many applications based on the Wi-Fi, Zigbee, Z-Wave, and Bluetooth protocols have been described in the literature, but there are still many connectivity and communication challenges to be faced regarding interoperability of the connected devices, bandwidth consumption, devices self-monitoring and self-management, power consumption [15].

Another relevant topic addressed by computer scientists, engineers, and home automation experts is the SH system architecture. Since this particular feature is determined by the way smart objects communicate with one another and by the way they gather and exchange information, there is not a single, widely accepted SH architecture: Instead, many studies focused on different types of IoT-enabled architectures [16].

Moreover, IoT evolution also brought up new challenges related to privacy and security. SHs, smart grids, and smart objects can be vulnerable to a variety of attacks because of the ways in which data are transmitted. Hence, research focused also on security protocols and policies at any level of the SH architecture including perceptual, network, support, and application layers [17, 18].

Finally, the potential of IoT has been exploited also in relation to health care [19], especially thanks to monitoring of patients' physiological information (e.g., blood pressure, heart rate, respiratory rate, weight, pulse rate, galvanic skin response) [20] and data gathered from monitoring their activities within an environment [21]. The systems managing these measurements that include personal and sensitive data can be also exposed to hacking risks.

In spite of many technological advancements in all the above-mentioned fields, some social-related concerns still exist that could hinder the large-scale adoption of IoT-based SH and thus of smart cities. A first set of problems can be identified with a distancing of SH technologies from humans: A SH was originally defined as a product for the home automation, a system in which the deployed devices are able to cooperate in order to anticipate and respond to the needs of their users. Research in the field of SH within the context of the smart city seems to be focused instead on other challenges (e.g., sustainability and saving energy) and partially forgets its initial purpose, i.e., fostering residents' well-being, with particular attention for frail segments of population [22, 23] (as highlighted also by the recent idea of "Human Smart City" [24], a paradigm trying to put human actor back at the center of this research field).

This set of problems is strictly connected to other critical issues related to the SH: the sense of privacy of users and SH technology adoption by its end-users. However, it is essential for a SH to manage the variety of data produced within its environment. Moreover, IoT SH technologies massively rely on inhabitants' monitoring: Inhabitants are monitored while performing their activities via a network of environmental sensors; data regarding their health condition are gathered via wearable sensors and fed into AI algorithms to provide customization of services; the interactions between residents, smart objects, and the domestic environments are stored, elaborated, and further investigated by clinicians, caregivers, automation experts. The possibility of providing personalization of services comes with a cost: the potential loss of residents' privacy within their domestic environments. Relying on monitoring technologies may rise some concerns in the end-users and ultimately hinder the adoption of the SH technologies on a large scale: As highlighted in different works [25, 26], privacy and intimacy represent a serious concern for the successful integration of IoT AAL solutions into domestic environments. These concerns are common to all SH and IoT-based AAL applications and represent "archetypal" concerns [27]. Furthermore, concerns regarding data sharing (due to the heterogeneity of the different SH devices) and perceived loss of control have also been reported in relation to energy-saving technological solutions [28, 29]. These concerns are more evident in older segments of population, which can face issues related to stigmatization and ageism, which also have a relevant impact in the adoption of AAL and assistive technologies [30].

To overcome these limitations, our research group designed the SHCLE Lab, a living laboratory that follows a human-centric IoT approach. In SHCLE, the attention is focused on Semantic Web to provide a holistic and detailed representation of the inhabitants, their needs, and their wishes. Furthermore, the adoption of Semantic Web fosters the semantic interoperability of data among different devices, thus tackling one of IoT technological issues. Finally, SHCLE deploys a set of digital solutions dedicated to the enhancement of residents' well-being, comfort, and health care by providing tailored services and leveraging on a soft monitoring of indoor human activity.

The reminder of this chapter is organized as follows: Sect. 2 introduces the semantic-based technologies on which SHCLE relies delving into the middleware-enabled communication among smart objects and into the set of ontologies adopted. Section 3 introduces the digital and virtual reality-based applications deployed within the SHCLE, highlighting the role of semantics in the domestic environment with a use case. Section 4 discusses some of the achievements and limitations of the proposed approach, while Sect. 5 presents the main conclusions of the chapter.

2 The Smart and Human-Centred Living Environment Experience

The SHCLE Living Lab simulates a SH, and it is located in Lecco (Lombardy, Italy), within the premises of the Institute of Intelligent Industrial Technologies and Systems for Advanced Manufacturing (CNR-STIIMA). SHCLE combines Semantic Web technologies and digital applications for AAL—including hardware and their connections with the semantic knowledge base—into a prototypical system. This prototype allows testing various resident-oriented functionalities in a quasi-real environment (Sect. 3 provides some examples). SHCLE system is thought as a knowledge-based system, which allows to expand its functionalities and applications by modeling some of their features into the semantic knowledge base. By leveraging on semantic representations of relevant concepts and data, AAL and digital applications can exchange data with the semantic models to customize the services they provide—thus offering inhabitants tailored solutions.

The technological backbone of SHCLE system is Semantic Web, a discipline characterized by "two main souls," and is strictly related to IoT. On the one hand, it leverages data model to foster semantic interoperability of information (among different data schemes and devices). On the other hand, it provides logic-based models of domains of knowledge, which can be enriched through automatic reasoning processes.

In the following paragraphs, it is reported an in-depth look at the semantic approach characterizing SHCLE, delving into the issue of data interoperability and providing a description of the knowledge base adopted.

2.1 Semantic Middleware

Modern domestic devices are projected into a new era in which they will be capable of exploiting the IoT protocol in its full potential. Leveraging this potential, devices will become dynamic networks comprising different kinds of resources, which will together form a sort of "nervous system" within the SH [31]. In particular, thanks to the advanced communication and networking capabilities provided by the IoT, each device connected to the IoT network will be able to propagate their relevant information within the domestic network to keep other interested components (data consumers) informed on particular events (e.g., a change of component's status, properties, and history) on which they want to be updated. The received information will be exploited by their consumers to react to the raised events (e.g., performing processes that in turn trigger actions or create services). Under these conditions, the domestic devices can turn into context-aware, interactive, and active participants of operational processes within the SH.

The above-mentioned futuristic scenarios involving collaborative devices can be realized with several studies conducted in various fields, ranging from AI to information and communication technologies. The current state of the art shows significant accomplishments, which allow to make these devices smarter and closer to the needs of the home dwellers [32]. However, one relevant issue remains to be investigated in order to realize these scenarios in their full potential. This issue is represented by the low level of interoperability of the different types of devices distributed within a domestic environment. Indeed, while the modern devices generate more and more data, still this massive amount of data is typically represented using different formats and nonaligned structures [33]. Under these conditions, these devices can encounter significant interoperability issues which hinder the efficient sharing and exchange of the data between data producers and data consumers, thus also exposing the latter collaboration. In addition, this already disorganized scenario is degraded by the lack of widely accepted standards.

This open issue has been addressed within SHCLE, with the goal to investigate and select a valid model of interaction among devices distributed within the domestic environment, regardless of the formats of the managed information by these devices. In particular, within SHCLE, it has been realized and evaluated the Semantic

Events Notifier (SEN) [34]. The latter is a message-oriented middleware combining agent-based technologies and Semantic Web technologies to offer services for the information propagation in near-real time among the devices connected to an AAL system. Specifically, this solution represents one of the major results of the Italian research project Design for All [35]. It is a publish–subscribe middleware where the requests from the data consumers to register to receive new relevant information and the notifications of new information toward the consumers are semantically enriched according to a shared semantic model (Fig. 1). Indeed, to overcome the issue represented by the scarce interoperability, SEN leverages a semantic data model. Such a model offers a shared representation and understanding of the information exchanged among different devices, thus allowing to seamlessly integrate and synchronize various data sources. Moreover, it allows to virtualize the physical home environment in a digital representation. This virtualization is enforced through the use of an agent-based approach that enables to abstract the complexity of controlling the collaborating devices. Specifically, leveraging the shared semantic data model, the requests of subscription are represented under the form of SPARQL queries, while the notifications are under the form of RDF language (Fig. 1). Moreover, the changes applied to the semantic model are expressed using the syntax of SPARQL UPDATE language and performed against the service of SPARQL end point provided by the RDF store which hosts the semantic model.

Under these conditions, SEN supports the combination of physical devices and their digital twin in a network of collaborative components. For this reason, the SHCLE can be seen as a cooperative cyber-physical system [36], where the information coming from the real devices can be distributed, shared, and understood by any other device connected to the system.

To test and validate the functionalities offered by SEN, the requirements of several demonstration scenarios have been elicited, with the aim to represent habits and activities which occur on a regular basis behind home walls. Some examples of these scenarios are reported in Sect. 3. Moreover, an evaluation of the SEN's performance

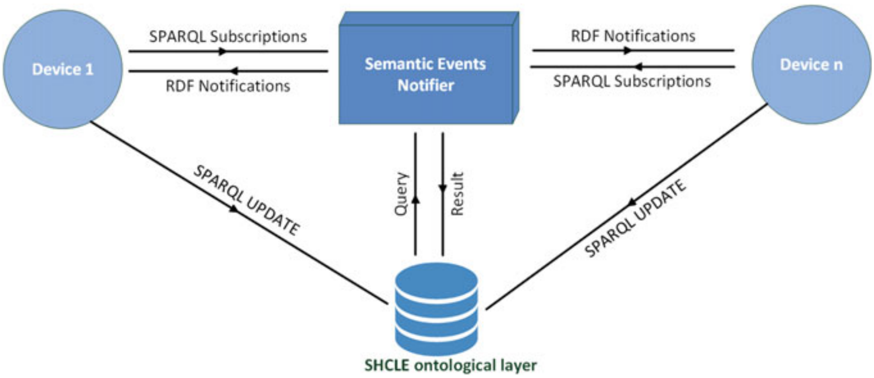

Fig. 1 A picture representing the semantic event notifier and its general architecture

in terms of its latency and scalability has been performed simulating a real case study [34]. Tests showed acceptable latency and the possibility to manage large volumes of data.

Besides the Design for All platform, SEN's functioning has been also integrated, extended, and tested with the CasAware platform [37], an AAL system which aims at optimizing energy consumption of an average family of three persons which includes people with impairment, also leveraging collaboration among appliances and devices. In addition, SEN has been integrated with other external IoT platforms leveraging approach of the European research project INTER-IoT [38]. One example of such an integration consists in the meteorological observation platform. Consequently, this integration allows to adjust the living environment parameters (e.g., indoor temperature and illuminance) in response to the available meteorological data.

2.2 Ontology as SH's Knowledge Base

The ontology is defined as an explicit, shared, and formal conceptualization of a domain of knowledge and of the relationships of the concepts composing a domain [39] and is one of the cornerstones of the Semantic Web. This technology has been widely adopted to model domain knowledge in a variety of research fields leveraging description logic-based languages, since it represents a promising approach for managing information (even if it comes from different sources). Ontology can also enable Semantic Web reasoning processes, which allow to discover new knowledge, in the form of pieces of information inferred from those modeled in the knowledge base. Therefore, reasoning processes can enrich the ontology itself with inferred knowledge. For this reason, ontology has been adopted as a backbone of many decision support systems [40] in different fields, including clinical decision-making.

As discussed in Sect. 2.1, Semantic Web gathered consensus as a promising tool to address the diversity of the "Things," and for this reason researchers dedicated a significant effort in the formalization of ontologies dedicated to IoT [41]. Also, in the fields of AAL and SH there exist several examples of ontologies developed to provide descriptions of particular portions of these domains. In these multidisciplinary fields, ontologies can be efficiently exploited to connect concepts belonging to different domains (e.g., person, environment, and appliances) in a coherent knowledge base. Other works are specifically dedicated to capture the knowledge of certain aspects of the SH, such as human activities within the environment [42], inhabitants' health status and preference modeling, appliances and smart object models [43], indoor comfort metrics, and more general SH architectures. The authors of [44] provide a survey of these ontologies. Within the SH, the possibility of inferencing new data can be used to trigger the actuation of services, while in AAL this semantic feature can foster the adoption of recommender systems or decision support systems. Therefore, researchers adopted ontology-based intelligent systems in a variety of contexts and

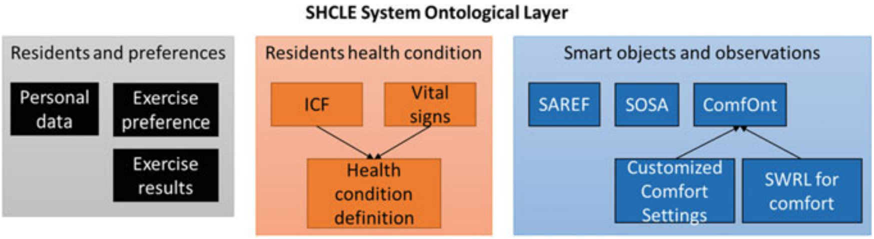

Fig. 2 A schema illustrating the main domain ontologies involved in SHCLE ontological layer and some of the main modules composing them

applications, ranging from health data management [45] to therapy personalization [46], and from physical activity recommendations [47] to diet suggestions [48] for specific segments of the population.

As an ontology-based SH architecture, SHCLE leverages different ontologies to provide logic-based descriptions of concepts deriving from several domains of knowledge. In fact, SHCLE exploits semantic models of (a) the inhabitant, (b) his/her health condition, and (c) the appliances deployed in the environment to describe the "main actors" of the SH. In addition to these models that are exploited in each AAL application deployed in SHCLE, the ontological layer also makes use of specific application ontologies (models developed specifically for supporting an application or achieving a task [49]) dedicated to relevant portions of other domains of knowledge (e.g., some of the comfort metrics relevant for indoor environments, a list of vital signs being monitored during physical exercises, and an excerpt of a cookbook for diet personalization). Following the guidelines provided by the majority of ontology engineering methodologies [50], one of the fundamental principles of Semantic Web is the reuse of already developed and validated ontologies. For this reason, SHCLE ontological layer relies on existing models to describe the main domains of interest. Furthermore, when developing new ontologies, it is fundamental to involve domain experts during both the conceptualization and the development phases of new models: SHCLE application ontologies were developed following this principle, to ensure a proper, sound, and complete representation of those portions of the domains of knowledge relevant to the applications.

SHCLE ontological layer (represented in Fig. 2) is developed with W3C-endorsed languages Resource Description Framework (RDF) [51] and Ontology Web Language (OWL-DL) [52], with rules written with Semantic Web Rule Language (SWRL) [53].

2.2.1 Residents and Their Preferences

Modeling the inhabitants and their personal data reuses the Friend Of A Friend (FOAF) vocabulary [54], created with the purpose of describing people and their identity, the organization they work in, and their contacts to facilitate personal information exchange on the Web. FOAF provides the means to represent first name, surname, data of birth, and age of each resident in a very straightforward way. Each resident is simply represented as an individual of the class foaf:Person, with properties such as foaf:firstName, foaf:lastName, foaf:birthday, and foaf:agent to describe some common features and contact information (foaf:phone and foaf:mbox). Although this is a very basic way to represent an inhabitant, FOAF still provides an efficient set of properties to formalize dwellers' personal information.

The modeling of residents is completed with a set of information related to their preferences when they perform exercise within their home. Each inhabitant is associated with the devices he/she prefers for physical training (i.e., ergometer or treadmill) and the visualization device (i.e., TV or PC screen or head-mounted display). The results from exercise sessions are also stored in this ontological layer by associating each resident to his/her sessions, which are linked to the general results gathered.

2.2.2 Resident's Health Condition

The representation of resident's health condition covers a pivotal role in any semantic AAL application deployed within the SHCLE. Considering the nature of the SH that provides tailored services and helps inhabitants to cope with their impairments, the possibility of describing dwellers and their health condition in a holistic way allows providing more personalized and efficient services. Thus, health condition's formalization must be able to describe with the appropriate level of detail the physical, cognitive, and physiological status of a person over time, in order to know his/her abilities in the environments where he/she lives. This model must also account for the potential cognitive decline occurring with aging. Furthermore, health condition definition should use a language that is understandable by any type of clinical personnel and other healthcare stakeholders, such as caregivers and social workers.

These reasons are at the base of the adoption of the International Classification of Functioning, Disability and Health (ICF) [55], a World Health Organization (WHO) standard framework aimed at providing a comprehensive tool for the description of an individual's health and its related statuses. Rather than focusing on specific diseases, the ICF provides a conceptualization of the functioning of an individual as a dynamic interaction between an individual's health condition, the environments in which he/she acts, his/her needs, attitudes, wishes, and preferences (personal factors). Due to its vocabulary, the ICF acts as a framework to ease communication and information exchange among different health stakeholders.

ICF is organized in four main components: "body functions" indicated with the letter "b," "body structures" indicated with the letter "s," "activity and participation" indicated with the letter "d," and "environmental factors" indicated with the letter "e." Each of these components can be further detailed into domains, which narrow the component to better identify the kind of problem addressed. A category is a code obtained by adding digits to the letter indicating a component (i.e., a code in the form of "letter#####"): A category can have up to five digits, and the higher is the number of digits, the more detailed the level of granularity adopted in the description of the health issue is. To represent the impact of an impairment, or the presence of an environmental or social barrier, the ICF provides a set of qualifiers, whose purpose is to detail information regarding the categories. Qualifiers can vary according to the component they are associated with, but generally they can range from 0 (meaning "no impairment" or "no barrier") to 4 (meaning "complete impairment" or "complete barrier"; +4 means "complete facilitator"), while digits from 5 to 9 cover specific component-dedicated functions. A health condition can be therefore represented considering the categories of interest for each specific subject, together with the qualifiers that specify and valorize each category. For instance, the category b3100.2 indicates a moderate impairment in those functions related to the production of sound made through the coordination of the larynx and the muscles of respiratory system. Similarly, s73000.412 suggests a complete impairment (first qualifier) in the bone structure of the arm, caused by a total absence—like in the case of an amputation (second qualifier)—of the left arm (third qualifier).

The ICF has been formalized into a formal ontology [56], which is adopted in different AAL and context-aware applications, ranging from smart environment characterization [57] to tourism [58], and from Return to Work [59] to assistive technology development [60].

It is worth noticing that relying on this WHO standard allows the clinical personnel to keep a central role in the definition of a resident's health condition, as they can interact using a "common language" and cooperate to the modeling process. Furthermore, by leveraging on consolidate ontology design patterns [61, 62], SHCLE facilitates the possibility to update an inhabitant's health condition, e.g., modifying a qualifier, and adding or deleting a category.

The description of a resident's health condition is completed with the modeling of basic physiological measurements: blood pressure, body temperature, respiration rate, heart rate (HR), oxygen saturation (SpO_2). This information is modeled into an application ontology, loosely based on the Vital Sign Ontology [63], which also contains information related to the exercise intensity an individual can sustain (these data are provided by clinical personnel). This ontology is therefore necessary to provide customized services related to physical exercises for the residents.

2.2.3 Smart Objects and Their Observations

The modeling of smart objects and their measurements and observations exploits two different ontologies. The Smart Appliance Reference (SAREF) [64] is an ontology developed as a result of a European research project in close collaboration with domain experts such as IoT experts, appliance manufacturers, stakeholders from the industry. This model provides the means to describe different types of devices with appliances such as ovens, cooktops, refrigerators, HVAC system, sensors and actuators, and brown goods. Its first goal is the achievement of interoperability among different devices. The SAREF embraces different features that allow to describe a saref:Device according to its type (saref:Actuator, saref:Sensor, saref:Appliance, saref:Meter, saref:HVAC), the commodities it offers, the tasks it is able to achieve, as well as general information (regarding the manufacturer, the device model, and its state). The ontology also provides the possibility to represent devices' energy consumptions (with classes like saref:Power and saref:Energy) and the functions they can perform (modeled as saref:ActuatingFunction, saref:EventFunction, saref:MeteringFunction, saref:SensingFunction).

SAREF, whose purpose was not originally intended for IoT devices, models all the necessary concepts and properties to represent a wide range of IoT devices, and thus it is exploited in several IoT projects [65]. Furthermore, it also encompasses some concepts for the representation of some units of measurement (saref:UnitOfMeasure).

To properly represent sensors and actuators, together with their measurements, SHCLE relies on the Sensor, Observation, Sample, and Actuator (SOSA) model [66]. SOSA is a lightweight and self-contained part of the W3C Semantic Sensor Network ontology. It consists of a set of classes and properties to describe both sensors and actuators together with the feature(s) they observe and the samples and measurements (observations) they perform. SAREF and SOSA partially overlap, since they share some parts of the domains they represent; for example, the pairs of classes sosa:Actuator and saref:Actuator, and sosa:Sensor and saref:Sensor represent the same concepts, even if the two ontologies model these parts under different perspectives. However, it is interesting to underline that this feature can enhance semantic interoperability, since the two ontologies can be mapped reciprocally [67].

2.2.4 Application Ontologies for Indoor Comfort

The representation of indoor comfort metrics exploits the ComfOnt [68]. This simple application ontology (which partially overlaps with SAREF) allows to formalize the comfort metrics (as physical magnitudes) with the class comf:Comfort_Metrics (≡saref:Property) that are measurable by sensors and customizable by the inhabitants. ComfOnt enables the modeling of four comfort metrics: illuminance, air quality (CO_2 indoor concentration), temperature, and humidity rate.

ComfOnt represents the four comfort metrics as a class and provides the means to model resident-based specific values for each of them. An individual belonging to the class comf:CustomizedComfort_Settings can be specified for each inhabitant, and it is further detailed by the class comf:Specification and its individuals (including its detailed subclasses, such as comf:IndoorIlluminance_Specs). Figure 3 exemplifies a comf:CustomizedComfort_Settings individual with an excerpt in Manchester OWL syntax [69].

These comfort specifications related to indoor illuminance are thought to ease the visual impairment of a resident characterized by visual impairment, providing him with enough illuminance to allow to perform daily tasks within his domestic environment. In this case, the illuminance can range from a minimum of 350 lx to a maximum of 750 lx.

The comfort specifications are also classified as "Acceptable" or "Unacceptable," according to the values specified by the resident. These values are compared to

```
/**
* @rdfs:comment An excerpt of ComfOnt illustrating a Customized Comfort Setting.
*
*/
Individual: comf:MrResident_CustomSet
    Types:
        comf:CustomizedComfortSetting
    Facts:
     comf:specifiesIlluminanceValues  comf:Parkers_Illuminance_Specs

Individual: comf:Parkers_Illuminance_Specs
    Types:
        comf:IndoorIlluminanceSpecs
    Facts:
     comf:MAX_IlluminanceValue  "750"^^xsd:int,
     comf:MIN_IlluminanceValue  "350"^^xsd:int
```

Fig. 3 An excerpt of ComfOnt ontology describing the individuals composing the customized comfort settings

```
/**
* @rdfs:comment Description of unacceptable CO2 specification.
*
*/

Class: comf:UnacceptableIndoorCO2Specs:
 EquivalentTo:
  comf:CustomizedComfortSettings and comf:MAX_CO2Conc_level only xsd:decimal[> 1000.0]
```

Fig. 4 Restriction developed to identify the CO_2 concentration values that do not satisfy thresholds imposed by regulations

the minimum and maximum thresholds provided by national (Italian) and European regulations for each of the four comfort metrics. For instance, if a resident (or a caregiver) specifies a value of 2377 ppm for the maximum CO_2 concentration acceptable in his/her domestic environment, the specification is inferred to be a comf:UnacceptableIndoorCO2Specs due to the following restriction of the class—which models the maximum value of CO_2 concentration for a domestic environment as specified by Italian regulations. Figure 4 illustrates the restriction.

2.2.5 Using Rules to Customize Indoor Comfort

SHCLE ontological layer is completed with a set of SWRL rules that allows to describe what happens within the smart environments when specific situations are detected by the sensors. These rules can be used to customize indoor comfort metrics according to the specification modeled in ComfOnt by the resident. An example, dedicated to an inhabitant characterized by a moderate impairment in the quality of vision (ICF code b2102.2), is provided by the SWRL rule depicted in Fig. 5.

This rule considers both the inhabitant's health condition and his/her personalized comfort settings modeled to help him/her overcoming the impairment. When the resident is detected (via a presence sensor) to be located in a room, the illuminance of the room is automatically set to the value required by the resident.

```
Person(?d), isInHealthCondition(?d, ?hc), HealthCondition (?hc), isDescribedBy (?hc,
?des), HC_Descriptor(?des), involvesICFCode (?des, b2102), Quality_of_vision (b2102),
hasQualifier (?des, ?q), swrlb:greaterThanOrEqual (?q, 2), isLocatedInRoom (?p, ?r),
Room(?r), Lighting device (?light), isLocatedIn (?light, ?r), IndoorIlluminanceSpecs
(?ill), MIN_IlluminanceValue (?ill, ?x), ExternalIlluminance (?exill),
hasMeasurementValue(?exill, ?m), swrlb:lessThan (?m, ?x) -> setsLighting (?light, ?ill)
```

Fig. 5 A SWRL rule that helps a resident (characterized by a moderate vision impairment in "quality of vision") to set indoor lighting taking into account the amount of illuminance-detected outdoor

```
Person(?d), isInHealthCondition(?d, ?hc), HealthCondition (?hc), isDescribedBy (?hc,
?des), HC_Descriptor(?des), involvesICFCode (?des, b440), Respiration_functions (b440),
hasQualifier (?des, ?q), swrlb:greaterThanOrEqual (?q, 1), isLocatedInRoom (?p, ?r),
Room(?r), Sensor(?sen), madeObservation (?sen, ?obs), Observation (?obs), hasSimpleResult
(?obs, ?r), CustomizedComfortSetting (?ccs), MAX_CO2Conc_level (?ccs, ?y),
swrlb:greaterThan (?r, ?y)-> OutOfComfortCO2Obs (?r)
```

Fig. 6 A SWRL rule to classify the CO_2 values detected within a room as within or outside the comfort settings provided by the inhabitant

In a similar way, SWRL rules can actuate the comfort metrics specified by the inhabitant also for the other comfort metrics.

SWRL can also be used to communicate the dwellers when a discrepancy in a comfort metric is detected by sensors. As an example, the SWRL rule reported in Fig. 6 classifies a measurement as exceeding the comfort level specified by the resident for the CO_2 concentration.

In the case depicted by this rule, if the observation performed by the sensor is found to exceed the value for CO_2 concentration provided by the resident, the observation is inferred to belong to the class comf:OutOfComfortCO2Obs, which triggers an alert via the graphical user interface to be delivered by the resident.

3 Virtual Reality-Based Applications for Assistance and Rehabilitation at Home

Virtual reality (VR) and digital technologies in general have recently become more and more common in daily life. While VR use was originally limited to entertainment (e.g., video games), nowadays several fields are fruitfully employing this technology [70]. Among others, there is the sector of AAL, which exploits it for both the development of assistive devices and the implementation of rehabilitative interventions at home.

Though rehabilitation is not usually considered strictly part of AAL, nowadays implementing the paradigm of "continuity of care" is getting more and more important [71]. As the worldwide population is growing old and life expectancy increases, National Healthcare Systems must face a deep reorganization of their services and prepare to adapt to the increasing needs of individuals affected by age-related and chronic conditions, while considering both limited costs and resources [72].

In such a context, the SH of the future must be ready to integrate both solutions supporting the users while accomplishing the activities of daily living, and solutions addressed to improve or maintain their health status, thus avoiding the deterioration of physical and cognitive functions [73]. SHCLE follows this principle. Therefore, it addresses the needs of the dwellers both in terms of daily assistance and in terms of provision of rehabilitation exercises. Two examples are reported in Sects. 3.1 and 3.2, respectively.

3.1 Domestic Environment Assistant

SHCLE system can be interacted with an application acting as a digital assistant for the residents: By using it, inhabitants can have access to SHCLE's services, including indoor comfort management and the performance of physical activity.

The Domestic Environment Assistant (DEA) is a digital application providing a graphical user interface (GUI) that was developed with Unity 3D [74], as a development of the Home Interactive Controller prototype [75]. DEA can be interacted via tablet, smartphone, or any plain surface of the house, such as a table or a kitchen worktop, by using a projector equipped with an infrared emitting laser unit for detecting multi-touch. The projector is connected to the main computer station inside the domestic environment.

Although elderlies are becoming more familiar with mobile applications [76], the possibility to project the GUI could drastically ease the interaction between elderly people and the SHCLE system, since it provides a wider display. Furthermore, this feature allows the residents to use DEA even if they are engaged in other activities, e.g., while they are cooking and their hands are dirty, or when they are using some tools and cannot use a mobile device with two hands. DEA also offers the possibility to access its functionalities from a mobile device via a client–server architecture. In this way, it can support residents with motor disabilities, who may face difficulties in moving from one room to another.

DEA's graphic is simple and minimal, and it has been designed to be intuitive for any user. The current functions deployed in DEA include comfort management for the domestic environment, calendar, a prototypical cookbook, and access to physical or rehabilitative exercises (Sect. 3.2). DEA receives changes applied to data from the ontological layer of SHCLE via SEN and provides residents with the means to modify the status of some appliances and actuators recurring to the same middleware. Figure 7 depicts DEA's splash page, from which the inhabitant can select the service he/she desires.

To help residents characterized by vision-related disabilities, DEA is provided with some functionalities that can adapt its appearance. For instance, as soon as the resident with a severe vision impairment like b2100—visual acuity functions—or b2102—quality of vision—requiring DEA's adaptation is detected by the presence sensor, the user's health condition is retrieved and sent to DEA to adapt its features. In this regard, DEA uses the SEN's features by registering itself through a SPARQL

Fig. 7 Homepage of the domestic environment assistant

query to be notified when some specific event occurs. In this case, the event consists in the presence of a resident and this information is in turn produced by the presence sensor and paired with the user's health condition. Once the event is triggered, the GUI switches to its "high contrast mode," which modifies the graphical representation of GUI's content in such a way that it only encompasses black and white icons, with white text on a black background.

3.1.1 Using DEA to Manage Indoor Comfort

By recurring to the information modeled in the ComfOnt ontology, whenever one of the measurements regarding an indoor comfort metrics is detected to be outside the comfort range set by the resident (or his/her caregiver), DEA provides the user with an alert (as presented in Fig. 8).

The warning sent to the user is in the form: "[A comfort metric] measured in the [room] is outside the preferred ranges: do you want to activate/turn off [actuator]? Yes/No." By tapping "Yes" on the surface or on the mobile device, the resident operate via SEN to activate the device(s) and restore the comfort settings. In any case, unless otherwise specified by the caregiver, the dwellers can always manually modify temperature, humidity rate, and illuminance within the limits provided by the regulations (and modeled in ComfOnt).

To help dwellers with cognitive disabilities, SHCLE also allows for the automatic actuation of the indoor devices every time a measurement of a comfort metric exceeds the ranges modeled in ComfOnt, thus avoiding the alert messages from DEA. This feature can be particularly helpful to ensure a comfortable domestic environment without burdening the residents or their caregivers with reading warnings and/or

Fig. 8 The DEA alerts the resident that detected temperature is outside his/her comfort range and asks him/her whether he/she wants to activate the air-conditioning system

taking decisions and not requiring them to move to DEA's surface or fetching the nearest mobile device.

3.1.2 Calendar and Medication Alert

DEA provides a calendar service, which allows residents to take note of their appointments (e.g., a medical examination and a visit) and providing the possibility to set alerts reminding them to take medications (Fig. 9). This feature, which can be useful for people characterized by memory-related impairments, can be set up by caregivers for those dwellers that may have issues in reminding how often during the week and how many medications they have to take.

3.1.3 Prototypical Recipe Book Functionality

DEA can also provide assistance in preparing a dish, using the Recipe Book function. This functionality allows the user to select a dish (among appetizers, main course, sides, and desserts) and to follow the step-by-step preparation.

The first step illustrates all the ingredients needed for the dish, while the other steps delve into the sequence of actions that are required to complete the preparation. Each step is further detailed with a picture, while a short video illustrates the most difficult passages: The clips can be stopped, paused, and played back using three buttons located under the video frame.

Fig. 9 Calendar view of DEA, in which inhabitants (or caregivers) can take note of appointments and set medication reminders

There are currently 3 recipes inside the DEA Recipe Book (1 appetizer, “Bruschetta”; 1 main course “Breasola rolls”; and 1 side, “Mixed fresh salad”), all of which are cold dishes, but more can be added.

The Recipe Cook Book feature is still under development, as it requires the ontological layer to be updated with an application ontology related to food and recipe. This feature is thought to help residents who are characterized by specific food-related problems (e.g., food intolerance or allergies) in preparing dishes that do not harm their health. In this case, the Recipe Cook Book shows the resident only those dishes he/she can eat without risks for his/her health. This can be made possible by adding to the resident’s ontological description, the food-related condition he/she is affected by. However, the ICF does not provide sufficient means to describe this particular conditions and, therefore, resident’s health condition may be described including also some classes from the International Classification of Disease (ICD) [77], which would enable a proper representation of health food-related conditions. Figure 10 illustrates the use of the Recipe Cook Book prototypical functionality.

3.2 *Virtual Reality-Based Rehabilitative Applications and Systems*

As already mentioned, VR and digital technologies could bring many advantages to rehabilitation [78]. First of all, they allow for an ecological rehabilitation, thus facilitating the transfer of the acquired skills to real-life scenarios. Also, the relatively easy modification of the training environments permits customizing the treatments

Fig. 10 Prototypical recipe book function of DEA while being tested by a user: the DEA interface is projected while the user follows its instruction to prepare a recipe

according to the subjects' needs and preferences, and to create different scenarios that could contribute in making the rehabilitation process (which often requires the repetition of the same exercise many times) less boring [79].

In addition, with the introduction of gaming or social elements, VR can contribute in stimulating residents' motivation, consequently increasing the adherence to the proposed treatment, even in an unsupervised environment, as the house [80]. Few studies have also demonstrated that being more motivated also leads to improved performance and therefore better recovery [81, 82]. Social elements can also contribute to support individuals from a psychological point of view, especially in situations in which sociality is reduced, e.g., when participation in the community life is lacking due to frailty, fear of going out, or if the person is limited in his/her autonomy.

Another relevant advantage is related to the possibility to measure, using objective variables and possibly integrating sensors in the VR application, the subjects' performances. On the one hand, this is helpful to provide the person who is rehabilitating with real-time feedback during the accomplishment of the exercise [83]. On the other hand, since performance outcomes are measured and elaborated, they could also be stored for keeping trace of the individual's progresses throughout the sessions. Therefore, this advantage allows the therapist to make more informed decisions regarding the administrated treatment [84]. Also, these two elements are essential especially when the rehabilitation intervention is to be administrated in an unsupervised environment.

Given this, the introduction of VR in rehabilitative treatments could appear straight. However, it must be remembered that any tool developed for health care cannot disregard an appropriate design phase, and a validation and certification phase [85]. The design must encompass the analysis of the specific needs of the patients and should be possibly carried out by a multidisciplinary team of both medical and technical personnel, in order to lead to the formulation of a user-centered solution responding to these needs.

The conjunct design phase that involves a different expertise and the customization of treatments, which takes advantage of the flexibility of digital environments, are all elements that could be optimized by the use of Sematic Web technologies. On the one hand, in fact, ontologies provide a shared language, whereas, on the other hand, they enable the formalization of each specific user health condition (as described in Sect. 2.2.2)—thus allowing to infer the best rehabilitative exercise, and also for its further customization (e.g., the level of difficulty and the technology with which the intervention is administered).

In SHCLE, the semantic description of the user's health status is used to select the most appropriate rehabilitative exercise, among the ones available up to now; the user can check the exercise instructions and its calendar (indicating the frequency, whether the exercise has been already performed or not, and the performance, whenever applicable, using DEA).

Currently, SHCLE includes VR-based exercises dedicated to: the cognitive training of subjects with mild cognitive impairment [86–88]; respiratory rehabilitation of elderly suffering from chronic obstructive pulmonary disease (COPD, [89]); rehabilitation of the upper limb of post-stroke patients [83]; the active aging of frail individuals [86]; and training of novel wheelchair users [59]. Though these applications may appear very different from each other, they all respond to the needs of chronic patients, for whom the continuity of care is essential to try to halt the progress of the disease and to prevent the occurrence of new symptoms.

3.2.1 Endurance Training for COPD: A Use-Case Scenario

As an example of the SHCLE solutions, a use-case scenario is presented. The use case depicts an elderly man, called John, suffering from moderate COPD. His health condition is formalized in the ontology (and encompasses moderate impairments to the following ICF categories: b440—respiration functions, b450—additional respiratory functions, b455—exercise tolerance functions, and b460—sensations associated with cardiovascular and respiratory functions). After a period of in-hospital standard respiratory rehabilitation, he is told by clinical personnel to continue his rehabilitation at home. In order to maintain the achieved aerobic exercise capacity, thus improving his overall condition, the physician and the physical therapist at the clinic recommend to perform daily endurance exercise. Endurance training, mainly cycling or walking, is one of the most common exercise modalities for COPD patients, able to improve exercise capacity and peripheral muscle function [90].

Based on his health condition, as represented in the ontology, John has access to the "Virtual Park" exercise. The "Virtual Park" is a VR-based application for respiratory rehabilitation developed to enable elderly patients with COPD to perform endurance training in a motivating and engaging scenario. The application has been developed to be easily adjusted to meet the needs of the specific patient. It allows the configuration of a training program, enabling the clinical personnel to set a predefined number of sessions and specific parameters for each session, including intensity and duration.

The virtual environment (VE) is a natural scenario representing a route in a park with realistic elements (e.g., flowers, animals, and a lake) and sound effects (e.g., birds singing and wind blowing). Such a naturalistic scenario has been selected to convey a pleasant feeling and to induce an "attentional shift"; i.e., the patient, by focusing on external stimuli provided by the VE, moves the attention away from negative internal feelings of breathlessness and fatigue. These elements, together with enhanced motivation, should improve the exercise tolerance and, as a consequence, the effectiveness of the training. Moreover, the application also provides the user real-time feedback on different phases of the exercise (e.g., warm-up, exercise, and cool down), the remaining time, the travelled distance, and the speed. A report is produced for each session including physiological response, self-reported symptoms (values of dyspnea and fatigue assessed before and after the training), speed and distance travelled. All collected data, including number of completed sessions, are elaborated and stored in the semantic repository, making them available to caregivers and clinical personnel for monitoring the patient's progress over time.

The VR application is integrated with a physical training device (e.g., a cycle ergometer or a treadmill) to perform the exercise and with wearable sensors (e.g., a wrist-worn pulse oximeter or a heart rate chest band) to measure the physiological response during the training session. Depending on the exercise prescriptions of the specific patient, the optimal intensity can be set on the training device. The exercise intensity can be configured acting on the treadmill speed or the cycle ergometer workload, depending on the selected device. This can be done in two different modalities: either acting directly on the speed/workload setting a predefined value that is kept constant throughout the session or calculating the speed/workload value in real time as a function of the heart rate, so that a target heart rate is maintained [89, 91]. Moreover, the solution can be deployed to different devices each providing a different visualization of the VE and, as a consequence, a different level of immersion: ranging from a PC or TV monitor to head-mounted displays (HMDs) [92].

The information provided by the ontology's resident module, the system configuration that best matches John's needs and preferences, is inferred. A first level of personalization concerns the exercise modality, the related physical training device, the physiological sensors, and the visualization device. Since John suffers from high levels of exercise-induced dyspnea, cycling is preferred for moderate/high training intensity [93]. In order to monitor the exercise-induced desaturation, John is recommended to wear a wrist-worn pulse oximeter able to measure SpO_2 not only before and after the session but also continuously during the session, thus ensuring that safety conditions are always met. John prefers to perform the training wearing an HMD: both because it allows for an easier setup configuration (he does not have

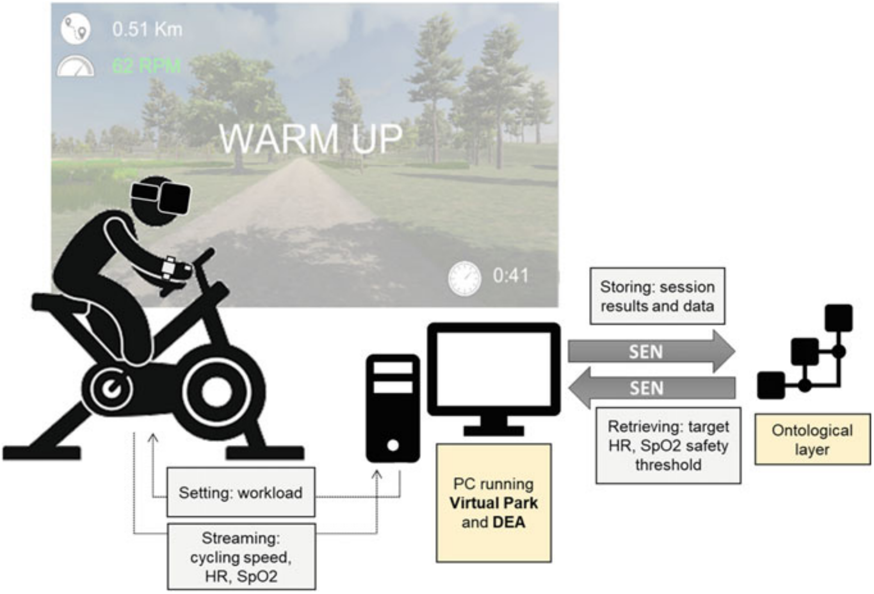

Fig. 11 "Virtual Park" system as configured for John: The SEN allows to retrieve data for customizing the training from the ontological layer and to store session results

enough space in the living room for placing the ergometer in front of the TV) and because he has already experienced immersive VR considering it more engaging. The system as configured for John is represented in Fig. 11.

The second level of personalization is related to the application configuration in terms of exercise parameters. Following the recommendations for exercise training in COPD patients, John is able to sustain a continuous training modality of 20 min, plus 2 min of warm-up and 2 min of cool down [90]. The ontology also provides the optimal exercise intensity, expressed here as the target HR, based on the assessment tests performed by the clinical team after the in-hospital rehabilitation period. Based on the HR measured during the 6-Meter Walking Test (6MWT), the target HR that John has to maintain is calculated [94]; this value is given as input to the VR application.

As previously mentioned, for each session, a report on the performance is generated including exercise-related parameters (in this case, cycling speed and distance travelled), physiological response (heart rate and SpO_2), and self-reported symptoms (dyspnea and muscle fatigue). Report data are then sent back through the SEN middleware to the semantic repository to update the patient's performances. They are available not only to John himself, but also to the physician and the physical therapist both for monitoring his health condition, possibly identifying risks of exacerbations, and for adjusting the training (e.g., increasing exercise duration), if necessary. Closing the loop toward the clinical personnel, while actively involving the patient, allows to strengthen the patient–doctor relationship, which represents a key factor for effective implementation of respiratory rehabilitation, and home-based rehabilitation in general [95].

4 Discussion

In this work, we introduced the Smart Human-Centred Living Environment system, from the backbone of CNR-STIIMA Lecco's Living Lab. This system leverages ontological representation of different domains of knowledge to provide residents with tailored services in the context of AAL and continuity of care. SHCLE system, by adopting the SEN semantic middleware, is able to ensure semantic interoperability of the information, while using semantic reasoning enables a less invasive approach different from inhabitants' monitoring. SHCLE includes digital applications, also based on virtual reality technologies, to provide the home inhabitants with a set of applications dedicated to support rehabilitative activities, and with DEA, an assistive system to help them modifying relevant features of their environment.

The proposed system is particularly significant in the field of AAL with the overall goal to move from a generic assistive approach toward technologies that take into account the specific needs of each dweller. The research and development works within SHCLE are still ongoing and will continue in the near future. First of all, future efforts will address the integration of new legacy devices within the SHCLE's infrastructure. Indeed, such devices are not initially conceived to use semantic model but they are typically based on proprietary data models and, for this reason, the integration of these devices could be a not trivial process. In order to enhance interoperability of these legacy systems and favor the adoption of the SHCLE approach on a large scale, it is essential to identify valid (also automatic) methods to semantically align each proprietary model with the adopted semantic model, through the harmonization of the respective differences [96]. Under such conditions, the semantic model plays the role of hub among the different models, thus contributing to the realization of a domestic data-sharing ecosystem where data can efficiently flow among the connected devices.

Future efforts of the SHCLE's researchers must be also addressed to preserve and guarantee the quality of the exchanged data within the defined data ecosystem [97]. In this regard, it will be essential to identify and apply efficient mechanisms to preserve the integrity of the data and to keep track of their provenance, for example representing this information into the ontology layer. In addition, the application of an edge computing approach can help to filter the data noise and the corrupted data, and eventually aggregate information, thus contributing to minimize the risk of congestion for the domestic network [98].

SHCLE solutions are thought for a single resident who lives alone and aims at living independently. However, some of the features of the described system can be easily adapted to a family of two or more members by leveraging RFID technology to identify different users (which would, in this case, carry a wearable sensor like a RFID bracelet). For instance, DEA appearance can be modified according to the dweller that is using it. Comfort settings can be adjusted only for a specific user, but different comfort settings can be actuated in different rooms of the house for different residents. Similarly, some of the physical exercises, in the case two or more inhabitants share the needs to perform physical activity with the same device, can be adapted to be performed with two devices at the same time, although personalization of the exercise features (e.g., workload and target HR) remains user-based. In this way, SHCLE is still able to adapt its services for specific users, but can foresee the possibility of managing the presence of two or more persons within the domestic environment.

Regarding the use of technologies, and of virtual reality (as the majority of the tools presented in the SHCLE system is developed with this technology), we have already discussed the advantages they could bring to AAL and continuity of care. However, to make these technologies really exploitable in home settings, at least two fundamental elements have to be considered.

The first regards the users, and it is their acceptance of technology [99]. As mentioned in Sect. 1, privacy concerns and the feeling of being monitored may hinder the use of technological services. Contrary to the most investigated IoT paradigms, SHCLE system does not rely massively on residents' monitoring. Instead, SHCLE limits the monitoring activity only to the data regarding resident's location within the domestic environment (i.e., in which room he/she is located) and monitors comfort metrics. Therefore, SHCLE shifts the attention to the environment, while leveraging knowledge regarding the inhabitant and his/her preferences to adapt services—since this approach does not require the dwellers (or their caregivers) to keep providing data to the system (with wearable devices or by being monitored). Moreover, SHCLE is expected to be considered less invasive than other IoT technologies. Furthermore, since SHCLE system's actuation mainly deals with everyday appliances such as HVAC system and hardware for performing physical activity, the risk of stigmatization and ageism is also expected to be considerably mitigated.

Besides the access to personal data or behavior, however, there exist other elements contributing to the acceptance of the new technologies. These are factors that go beyond the real effectiveness of the proposed means and that rather involve a more personal and subjective judgement. Psychological studies have identified them in the perceived meaningfulness of the instrument and its perceived ease-of-use [99]. Consequently, besides the real effectiveness of an application or a service, the user must: (1) perceive it as a help and (2) be able to access easily to the desired functionalities in order to obtain the wanted benefit, in order to start using it [100]. This concept can be further clarified with an example: If a senior does not feel like he needs a device to remember how to cook, because he is confident in performing such a task, he may consider such a functionality only as something remembering him he is old, not autonomous, and perhaps with some cognitive deficits. As a consequence, he will never use it. This short example shows how subjective variables can contribute to the (un)success of a specific technology, and how ageism and stigma may be two elements strongly influencing the attitude of elderly toward any technological support [101]. Adaptation to each subject's needs, and an appropriate introduction of the device made by explaining its potentialities, the information it requires, and how it can be used by anyone may be of help in reducing the occurrence of these issues. In the case of DEA, a point of strength is indeed the fact that it can be intended as a support by anyone, though to a different extent depending on each user's needs and health status, exactly as other commercial services (e.g., Amazon Alexa or Google Home). The same is worthy for the easiness of use: If the user is willing to use a specific system, but this one is not easily controllable, the final result will be the abandon of the technological support.

The second fundamental element influencing the use of technology and the effective implementation of the "house of the future" is related to the infrastructure [102]. Still nowadays, not everybody, and elderly in particular, owns a smart device or pays for an Internet connection. In the future, being able to support all the citizens, irrespectively from their social extraction, would mean being able to provide everybody with the same technological means, and the same possibility of accessing assisting/rehabilitative services. This requires each country to make an effort toward the digitalization of health care and build an infrastructure able to handle a big quantity of data in a secure and efficient way [103].

5 Conclusions

This chapter introduced SHCLE, a knowledge-based system aimed at enabling an IoT-based SH. The system leverages ontological representation of relevant pieces of information to provide residents with customized services, including management of indoor comfort, assistive technologies, and rehabilitative activities. By exploiting a semantic middleware, SHCLE can foster semantic interoperability among different smart objects deployed in the environment, thus enabling the AAL goal of assisting the inhabitants in some of their daily activities.

In the next future, the authors will work for the integration of new smart devices and new systems for the assistance and the rehabilitation of individuals suffering from different pathologies. Future works foresee also the integration of a RFID device allowing for the recognition of the user and the activation of his/her specific services, even in case of multiple dwellers. This approach will require facing an important issue, i.e., the implementation of conflict-solving rules when more than one user occupies the same spaces. This will constitute an essential step forward, as, only in this way, SHCLE can evolve further and become really able to respond to the needs of every member of the family.

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