COVID-19 as a Driver for Digital Transformation in Healthcare

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1   Introduction

The COVID-19 crisis had and is still having a huge impact on individuals, organizations, and society. Despite all the tragedy it caused, it also created room for learning and change. Previous important contributions to management and organization studies as well as to healthcare research were originally derived from extreme contexts such as wars, chemical leaks, aircraft accidents, nuclear disasters, or healthcare action teams (e.g., Hällgren et al. 2018). In their literature review on extreme context research, Hällgren et al. (2018) emphasized the potential for learning processes and development of new and innovative approaches in emergency contexts such as a pandemic.

Healthcare systems around the world struggle with rising healthcare expenditures, increasing staff shortages, and structural barriers to access (e.g., Christensen et al. 2009; Steinhauser 2019). Digital innovations and digital transformation, however, are perceived as an opportunity to improve the quality of and access to care while at the same time containing costs (Agarwal et al. 2010; Fichman et al. 2011). Yet, despite this potential, healthcare providers were quite hesitant in adopting and using digital innovations in the past. Thus, digitalization in healthcare progressed only slowly (e.g., Agarwal et al. 2010; Steinhauser 2020; Steinhauser et al. 2020; Venkatesh et al. 2011).

However, the COVID-19 outbreak, announced as a pandemic by the World Health Organization on 12 March 2020 (World Health Organisation 2020b), necessitated significant changes in healthcare delivery (see Fig. 1). First, social distancing was introduced all over the world in order to decrease the COVID-19 growth rate
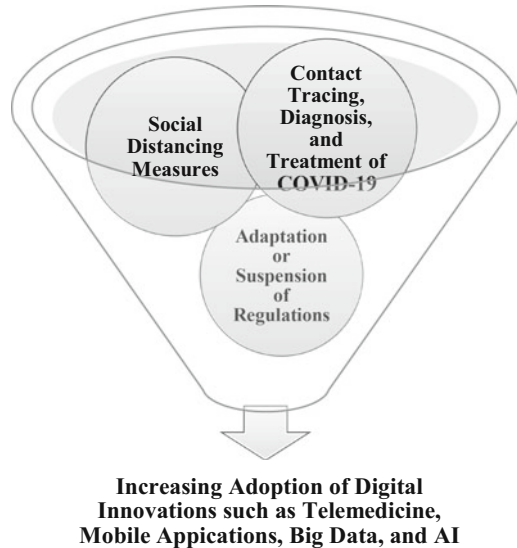
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93

Fig. 1 Factors driving the digital transformation in healthcare during the COVID-19 pandemic. Source: author

Increasing Adoption of Digital
Innovations such as Telemedicine,
Mobile Appications, Big Data, and AI

(e.g., Courtemanche et al. 2020). As a result, telemedicine experienced a strong increase in many countries. Second, digital technologies were employed to deal with the COVID-19 pandemic: Mobile applications, big data, and artificial intelligence (AI) were employed to trace, diagnose, and treat COVID-19 infections. Third, regulations were adapted or suspended in order to facilitate the use of these digital technologies. Thus, regulatory sandboxes for the adoption of digital technologies were created (Steinhauser et al. 2020; Tsai et al. 2020). The use of digital solutions helped to protect patients, healthcare professionals, and the population at large (Whitehouse and Marti 2020).

This chapter presents a non-exhaustive selection of examples from practice and thus utilizes a practice-oriented perspective to provide an overview of the various ways the COVID-19 pandemic accelerated the digital transformation in healthcare. By doing so, this chapter aims to illustrate paths for facilitating the diffusion of digital technologies in healthcare during the pandemic and beyond.

2   Telemedicine for Remote Care Delivery

Telemedicine is defined as the delivery of healthcare over distance by digital means (World Health Organization 2010). Telemedicine can consist of provider-to-provider as well as provider-to-patient applications and encompasses applications such as teleconsultation, telemonitoring, or teleradiology (e.g., Steinhauser 2020; Steinhauser et al. 2020). That way, telemedicine provides the opportunity to deliver healthcare remotely and thus supports social distancing measures during the COVID-19 pandemic.

Telemedicine solutions offer several benefits during a public health emergency such as the COVID-19 pandemic. Telemedicine can help to reduce the risk of infection for patients as well as healthcare professionals. It allows patients who have non-COVID-19 issues to receive care without the risk of exposure. For patients concerned that they have COVID-19, telemedicine can address questions, coordinate testing, and triage clinical needs. In addition, healthcare professionals who are themselves quarantined can continue to provide care via telemedicine. Furthermore, telemedicine can also free up resources such as hospital beds for patients in urgent need of care and limits the demands on emergency departments (Fisk et al. 2020; Hollander and Carr 2020; Mehrotra et al. 2020; Moazzami et al. 2020; Whitehouse and Marti 2020).

All across *Europe*, telemedicine applications such as teleconsultations reportedly experienced large growth rates (Whitehouse and Marti 2020): In Catalonia (*Spain*), 70% of healthcare encounters that were previously conducted face-to-face were transferred to digital encounters within a very short period of time. In *France*, healthcare providers and patients were incentivized to use telemedicine services by health authorities and insurers in order to expand its use across the country. The National Institute for Health and Disability Insurance of *Belgium* set a fee of 20 EUR for teleconsultation.

In the *United Kingdom*, the National Health Service (NHS) England issued a notice to health trusts, health service commissioners (procurers), and providers, including general practitioners (GP) services, calling for them to support the provision of telephone-based or digital- and video-based consultations, and advice for outpatients (Fisk et al. 2020; NHS 2020). In Scotland, the telemedicine development in relation to COVID-19 was swifter than in other regions of the UK, presumably built on experience that was driven by the needs of rural, remote, and island communities. Its program included telemedicine applications such as home and mobile health monitoring, videoconferencing, and telecare (Fisk et al. 2020). Before the COVID-19 pandemic, video appointments accounted for only 1% of the encounters of Britain's NHS. This drastically changed in a matter of days. A London-based GP noted: "We're basically witnessing 10 years of change in one week." (Mueller 2020).

In *Germany*, telemedicine platform operators reported growth rates of more than 1000%. There was a drastic increase in teleconsultations. By the end of 2017, only 1.8% of physicians offered teleconsultations via videoconference. In May 2020, a study revealed that 52.3% of the physicians offered this telemedical service and another 10.1% planned to implement it at short notice. The trigger for this significant increase was the COVID-19 pandemic: 94.1% of the responding physicians stated that they introduced teleconsultations as recently as 2020, and 89.7% clearly attributed their adoption of teleconsultations to the COVID-19 pandemic (Obermann et al. 2020). In order to support the adoption of teleconsultations via videoconference, reimbursement regulations have been modified. As a result, teleconsultations were reimbursed on an equal footing with conventional face-to-face consultations by the German National Association of Statutory Health Insurance Physicians (KBV) (Whitehouse and Marti 2020). For the second and third

quarter of 2020, the cap for video teleconsultation of 20% of all a physician's cases was lifted. Furthermore, the process for obtaining a license for teleconsultation via videoconference has been temporarily simplified for this period (KBV 2020; KVB 2020).

In *Australia*, GPs have traditionally only been reimbursed for face-to-face treatment of patients. On 11 March 2020, however, the provision of teleconsultations for vulnerable groups such as elderly people, pregnant women, chronically ill persons, or immunocompromised persons for 6 months was unveiled by Australia's Medicare (Tanne et al. 2020). On 30 March 2020, the rollout of a universal telemedicine model for all Australians started to enable healthcare access through teleconsultations (with or without video) from home until 30 September 2020 (Fisk et al. 2020).

China, where the COVID-19 outbreak presumably started in Wuhan in December 2019, was the first country that had to deal with the new virus. In the Shandong province, for example, a telemedicine platform was initiated to deal with the COVID-19 pandemic. It includes a COVID-19 informational page, remote education for vulnerable individuals, and an online consulting clinic where experts are available 24 h/day. The telemedicine platform targets patients, medical staff, and community residents (Song et al. 2020).

In the *USA*, COVID-19 also has had a large impact on the adoption of telemedicine. For instance, NYC Health + Hospitals (NYC H+H), a large safety net healthcare delivery system in New York, reported a drastic increase in the provision of telemedicine services (Lau et al. 2020): Before the COVID-19 pandemic, NYC H+H served more than one million patients and provided less than 500 telehealth visits monthly. From March 2020, however, NYC H+H transformed their system by employing virtual care platforms. They conducted almost 83,000 teleconsultations in one month and more than 30,000 behavioral health encounters via telephone and video. In addition, they provided patient-family communication, post-discharge follow-up, and palliative care for COVID-19 patients using telemedicine. In this case as well, the adaptation of reimbursement regulation played a crucial role. The New York State Department of Health expanded Medicaid coverage and reimbursement of a greater range of telemedicine services. The swift shift to virtual care relied on historic regulatory changes enacted at the federal and state level in response to the COVID-19 pandemic. Within only two weeks or less, primary care practices around the country also transformed from in-person care to virtual practices with telemedicine (Mehrotra et al. 2020). Before the crisis, telemedicine played a minor role in many practices, but after COVID-19 hit, the majority of patient encounters were virtual. This transformation was clearly supported in the cases where temporary changes allowed the reimbursement of applications such as teleconsultations. The adoption of telemedicine by NYC H+H and primary care practices was also facilitated by pre-existing digital technologies such as an electronic health record (EHR) system and health information exchange (HIE) functionalities (Lau et al. 2020; Mehrotra et al. 2020; Salway et al. 2020). Thus, this crisis clearly provides support for the argument claiming the importance of digital complementary assets for telemedicine adoption (Steinhauser et al. 2020).

3 AI, Big Data, and Mobile Applications in the Context of COVID-19

3.1 Contact Tracing and Containment of COVID-19

Contact tracing is used to avoid the further spread of COVID-19 by identifying and managing people who have recently been exposed to an infected COVID-19 patient (Lalmuanawma et al. 2020). Contact tracing is an essential public health tool used to break the chain of virus transmission (World Health Organisation 2020a) and can contain the outbreak by increasing the chances of adequate controls and helping to reduce the magnitude of the COVID-19 pandemic. The digital contact tracing process can perform virtually in real-time. As a result, it is much faster than a non-digital system (Lalmuanawma et al. 2020).

Various countries around the world came up with mobile applications that utilize different technologies such as Bluetooth, Global Positioning System (GPS), Social graph, contact details, network-based API, mobile tracking data, card transaction data, and system physical address. These digital apps are designed to collect individual personal data that is analyzed to trace persons, and they use centralized, decentralized, or hybrid approaches. In addition, AI, more precisely machine learning (ML), can be employed for analyzing the data and making sense of big data (Lalmuanawma et al. 2020; Whitelaw et al. 2020). By 01 September 2020, 47 countries had developed COVID-19 tracing applications (O'Neill et al. 2020; Statista 2020). Below, two examples are described, respectively from Asia and Europe.

Singapore, which has maintained one of the lowest per-capita COVID-19 mortality rates in the world, developed a mobile application that records encounters of individuals and stores them in their mobile phones for 21 days. The application employs short-distance Bluetooth signals. Singapore's Ministry of Health can access the data when an individual is diagnosed with COVID-19 and identify contacts of the infected person (Whitelaw et al. 2020).

Germany launched a decentralized mobile application to be used on a voluntary basis. Individuals can decide whether they want to install the app on their smartphones, inform the application about a positive test, and how they proceed when they learn that they have been in contact with a COVID-19-positive individual. The app uses Bluetooth technology to measure the distance and duration of encounters between people who have installed the app. Encrypted IDs (random codes) do not disclose any information about the individuals or their location (Bundesregierung 2020).

However, digital technologies such as tracing applications can potentially infringe on privacy. Hence, government authorities have to balance the need for COVID-19 containment (or any other benefit for public health) with the individual's right to privacy and data security (Whitelaw et al. 2020). COVID-19 tracing applications can establish a basis of information and practical experience that provides insights for the setup of future digital health applications and can thus facilitate their adoption.

3.2   Diagnosis of COVID-19 Cases

Early detection and diagnosis of COVID-19 is critical because early treatment can save lives and limit the spread of the pandemic disease. During the COVID-19 pandemic, AI applications such as machine learning were used to augment the diagnosis of the disease by applying them to medical images such as CT scans and X-rays and to clinical blood sample data (Lalmuanawma et al. 2020).

Already before the COVID-19 pandemic, interest in ML-based technology for medical imaging had increased around the world. Through chest X-rays and CT scans, healthcare systems produced a large amount of data on COVID-19. Huge datasets from China and increasingly from other countries have generated numerous publications where AI applications are applied to COVID-19 (Bachtiger et al. 2020).

Ardakani et al. (2020) suggest a rapid and valid method for COVID-19 diagnosis by applying the ***deep learning*** (DL) technique to images of *CT scans* in order to distinguish a COVID-19 infection from non-COVID-19 groups. The authors used ten well-known pre-trained ***convolutional neural networks*** to diagnose infections related to COVID-19. The best performance was achieved by ResNet-101, which could distinguish COVID-19 from non-COVID-19 cases with an area under the curve (AUC) of 0.994 (sensitivity: 100%; specificity: 99.02%; accuracy: 99.51%). They conclude that the DL technique can be used as an adjuvant tool for diagnosing COVID-19.

Another study applied ***deep neuronal networks*** in order to achieve automated early detection of COVID-19 cases in *X-ray images* (Ozturk et al. 2020). Their DarkCovidNet model can assist clinicians in making a faster and accurate diagnosis by using heatmaps that can help the radiologists to locate the affected regions on chest X-rays. It produced a classification accuracy of 98.08% for binary classes and 87.02% for multi-class cases.

COVNet, an open-source ***deep convolutional neural network*** design developed in China, can quickly differentiate COVID-19 cases from other lung diseases using *chest CT scans*. The DL model can accurately detect COVID-19 and differentiate it from community-acquired pneumonia and other lung conditions (sensitivity: 87%; specificity: 92%; area under receiving operating curve (AUROC): 0.95) (Li et al. 2020).

A study conducted in China extracted *11 key blood indices* (bilirubin total, creatine kinase isoenzyme, GLU, creatinine, kalium, lactate dehydrogenase, platelet distribution width, calcium, basophil, total protein, and magnesium) through ***ML*** (random forest algorithm), which, as a COVID-19-discrimination tool, can assist healthcare professionals in making a rapid diagnosis. The tool achieved a sensitivity of 95.12%, a specificity of 96.97%, and an overall accuracy of 95.95% (Wu et al. 2020).

3.3 Treatment of COVID-19 Cases

In addition to diagnosis, AI can also help to identify patients that may progress into severe conditions. That way, healthcare professionals are able to intervene earlier and thus may save lives.

A study with patients from Shanghai (China) who have been diagnosed with COVID-19 employed *ML* (namely support vector machine) to analyze *laboratory features associated with severe/critical symptoms*. It identified a combination of four clinical indicators (age, GSH, CD3 ratio, and total protein) that predicts severe/critical symptoms of patients infected with COVID-19. The model is effective and reached an AUROC of 0.9996 and 0.9757 in the training and testing dataset, respectively (Sun et al. 2020).

ML algorithms, like one developed in China, can predict the likelihood of developing acute respiratory distress syndrome and critical illness among COVID-19 infected patients. As a result, these prediction models can guide clinical decision-making and timely intervention in critical cases. In addition, they can improve resource allocation for COVID-19 treatment (Whitelaw et al. 2020). Thus, AI-based tools can provide objective stratification tools to rapidly assess a patient, assisting healthcare professionals in making difficult decisions about the allocation of scarce resources (Bachtiger et al. 2020).

Furthermore, AI can potentially contribute to tackling the COVID-19 pandemic by supporting the *development of drugs and a vaccine* (Lalmuanawma et al. 2020; Naudé 2020). Beck et al. (2020) used a pre-trained *DL-based* drug–target interaction model called Molecule Transformer-Drug Target Interaction (MT-DTI) to identify commercially available *drugs* that could act on viral proteins of SARS-CoV-2, the virus that causes COVID-19. They employed the algorithm on the 3C-like proteinase of SARS-CoV-2 and 3410 existing FDA-approved drugs. The drugs Atazanavir, Remdesivir, and Kaletra were predicted to inhibit SARS-CoV-2. Ke et al. (2020) established an *AI platform* to identify potential existing drugs with anti-SARS-CoV-2 activities by using two different learning databases; one consisted of the compounds reported or proven active against SARS-CoV, SARS-CoV-2, HIV, and the influenza virus, and the other one contained the known 3C-like protease inhibitors.

Finally, Ong et al. (2020) applied reverse vaccinology and *machine learning* in order to develop an effective and safe *vaccine* against COVID-19, caused by the SARS-CoV-2 coronavirus. They conclude that their predicted vaccine targets (i.e., proteins that were predicted to be adhesins) have the potential for effective and safe COVID-19 vaccine development.

In summary, a crisis such as the COVID-19 pandemic can accelerate innovation, in part by creating permissive environments for collaboration between healthcare professionals and AI experts (Bachtiger et al. 2020). Nevertheless, there has to be a balance between risk and rapidity that helps to find the solutions with the greatest clinical value. In this crisis, governments increasingly advocated light-touch regulation. Together with robust ethical standards, this can help to create an

environment for a rapid and ethical approach. As a result, the COVID-19 crisis could mark the beginning of the digital transformation in healthcare through AI.

4   Conclusion

This chapter shows that crises such as the COVID-19 pandemic pose not only threats but also opportunities. As a result of the COVID-19 crisis, digital health solutions will likely present a more important complement to conventional care than before the pandemic. The adoption and usage of digital technologies during the COVID-19 pandemic created practical experience, technological capability, and medical evidence.

The COVID-19 pandemic had an impact on every stakeholder and individual, which got everyone involved in the fight. The rapid adoption of digital technologies during the crisis shows that stakeholders will be motivated to engage in the digital transformation in healthcare if each one can benefit from these digital innovations (e.g., Steinhauser 2019). It also points to the importance of digital complementary assets for a swift adoption of digital innovations such as telemedicine or AI (Steinhauser et al. 2020).

Finally, regulatory bodies and health insurances have temporarily modified long-standing regulations and policies to support the digital transformation during the COVID-19 crisis (e.g., Sinsky and Linzer 2020). In order to sustain these changes, healthcare systems should seize the opportunity to take advantage of the lessons of COVID-19 for the further digital transformation in healthcare.

References

Agarwal, R., Gao, G., DesRoches, C., & Jha, A. K. (2010). The digital transformation of healthcare: Current status and the road ahead. *Information Systems Research, 21*(4), 796–809. https://doi.org/10.1287/isre.1100.0327.

Ardakani, A. A., Kanafi, A. R., Acharya, U. R., Khadem, N., & Mohammadi, A. (2020). Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. *Computers in Biology and Medicine, 121*, 103795. https://doi.org/10.1016/j.compbiomed.2020.103795.

Bachtiger, P., Peters, N. S., & Walsh, S. L. F. (2020). Machine learning for COVID-19—Asking the right questions. *The Lancet Digital Health, 2*(8), e391–e392. https://doi.org/10.1016/S2589-7500(20)30162-X.

Beck, B. R., Shin, B., Choi, Y., Park, S., & Kang, K. (2020). Predicting commercially available antiviral drugs that may act on the novel coronavirus (SARS-CoV-2) through a drug-target interaction deep learning model. *Computational and Structural Biotechnology Journal, 18*, 784–790. https://doi.org/10.1016/j.csbj.2020.03.025.

Bundesregierung. (2020, August 07). Corona-Warn-App. Retrieved from https://www.bundesregierung.de/breg-de/themen/corona-warn-app/corona-warn-app-faq-1758392

Christensen, C. M., Grossman, J. H., & Hwang, J. (2009). *The innovator's prescription – A disruptive solution for health care* (1st ed.). New York: McGraw-Hill Professional.

Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., & Yelowitz, A. (2020). Strong social distancing measures in the United States reduced the COVID-19 growth rate. *Health Affairs, 39*(7), 1237–1246. https://doi.org/10.1377/hlthaff.2020.00608.

Fichman, R. G., Kohli, R., & Krishnan, R. (2011). The role of information systems in healthcare: Current research and future trends. *Information Systems Research, 22*(3), 419–428. https://doi.org/10.1287/isre.1110.0382.

Fisk, M., Livingstone, A., & Pit, S. W. (2020). Telehealth in the context of COVID-19: Changing perspectives in Australia, the United Kingdom, and the United States. *Journal of Medical Internet Research, 22*(6), e19264. https://doi.org/10.2196/19264.

Hällgren, M., Rouleau, L., & de Rond, M. (2018). A matter of life or death: How extreme context research matters for management and organization studies. *Academy of Management Annals, 12*(1), 111–153. https://doi.org/10.5465/annals.2016.0017.

Hollander, J. E., & Carr, B. G. (2020). Virtually perfect? Telemedicine for Covid-19. *New England Journal of Medicine, 382*(18), 1679–1681. https://doi.org/10.1056/NEJMp2003539.

KBV. (2020, August 30). *Videosprechstunden weiterhin unbegrenzt möglich - Andere Sonderregelungen enden*. Retrieved from https://www.kbv.de/html/1150_46724.php

Ke, Y.-Y., Peng, T.-T., Yeh, T.-K., Huang, W.-Z., Chang, S.-E., Wu, S.-H., Chen, C.-T., et al. (2020). Artificial intelligence approach fighting COVID-19 with repurposing drugs. *Biomedical Journal, 43*, 355. https://doi.org/10.1016/j.bj.2020.05.001.

KVB. (2020, August 30). *Videosprechstunde nach § 291g SGB V*. Retrieved from https://www.kvb.de/praxis/it-in-der-praxis/videosprechstunde/

Lalmuanawma, S., Hussain, J., & Chhakchhuak, L. (2020). Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review. *Chaos, Solitons & Fractals, 139*, 110059. https://doi.org/10.1016/j.chaos.2020.110059.

Lau, J., Knudsen, J., Jackson, H., Wallach, A. B., Bouton, M., Natsui, S., Chokshi, D. A., et al. (2020). Staying connected in the COVID-19 pandemic: Telehealth at the largest safety-net system in the United States. *Health Affairs, 39*(8), 1437–1442. https://doi.org/10.1377/hlthaff.2020.00903.

Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., Song, Q., et al. (2020). Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: Evaluation of the diagnostic accuracy. *Radiology, 296*(2), E65. https://doi.org/10.1148/radiol.2020200905.

Mehrotra, A., Ray, K., Brockmeyer, D. M., Barnett, M. L., & Bender, J. A. (2020). Rapidly converting to "virtual practices": Outpatient care in the era of Covid-19. *NEJM Catalyst, 1*(2), 1–5.

Moazzami, B., Razavi-Khorasani, N., Dooghaie Moghadam, A., Farokhi, E., & Rezaei, N. (2020). COVID-19 and telemedicine: Immediate action required for maintaining healthcare providers well-being. *Journal of Clinical Virology, 126*, 104345. https://doi.org/10.1016/j.jcv.2020.104345.

Mueller, B. (2020, April 4). Telemedicine arrives in the U.K.: '10 Years of Change in One Week'. *The New York Times*.

Naudé, W. (2020). Artificial intelligence vs COVID-19: Limitations, constraints and pitfalls. *AI & SOCIETY, 35*, 761–765.

NHS. (2020, August 17). *Video consultations for secondary care*. Retrieved from https://www.england.nhs.uk/coronavirus/publication/video-consultations-for-secondary-care/

O'Neill, P. H., Ryan-Mosley, T., & Johnson, B. (2020, September 01). *A flood of coronavirus apps are tracking us. Now it's time to keep track of them*. Retrieved from https://www.technologyreview.com/2020/05/07/1000961/launching-mittr-covid-tracing-tracker/

Obermann, K., Brendt, I., Hagen, J., Müller, P., & Stachwitz, P. (2020). Ärzte im Zukunftsmarkt Gesundheit 2020: Ärztliche Arbeit und Nutzung von Videosprechstunden während der Covid-19-Pandemie: Stiftung Gesundheit, health innovation hub des Bundesministeriums für Gesundheit.

Ong, E., Wong, M. U., Huffman, A., & He, Y. (2020). COVID-19 coronavirus vaccine design using reverse vaccinology and machine learning. *Frontiers in Immunology, 11*.(1581. https://doi.org/10.3389/fimmu.2020.01581.

Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Rajendra Acharya, U. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in Biology and Medicine, 121*, 103792. https://doi.org/10.1016/j.compbiomed.2020.103792.

Salway, R. J., Silvestri, D., Wei, E., & Bouton, M. (2020). Using information technology to improve COVID-19 care at new York City health + hospitals. *Health Affairs, 39*(9), 1601–1604. https://doi.org/10.1377/hlthaff.2020.00930.

Sinsky, C., & Linzer, M. (2020). Practice and policy reset post-COVID-19: Reversion, transition, or transformation? *Health Affairs, 39*(8), 1405–1411. https://doi.org/10.1377/hlthaff.2020.00612.

Song, X., Liu, X., & Wang, C. (2020). The role of telemedicine during the COVID-19 epidemic in China—Experience from Shandong province. *Critical Care, 24*(1), 178. https://doi.org/10.1186/s13054-020-02884-9.

Statista. (2020). *Covid-19 outbreak: Which countries are deploying coronavirus tracing apps?* Retrieved from https://www.statista.com/chart/22335/development-of-tracing-apps-by-country/

Steinhauser, S. (2019). Network-based business models, the institutional environment, and the diffusion of digital innovations: Case studies of telemedicine networks in Germany. *Schmalenbach Business Review, 71*(3), 343–383. https://doi.org/10.1007/s41464-019-00076-9.

Steinhauser, S. (2020). Enabling the utilization of potentially disruptive digital innovations by incumbents: The impact of contextual, organisational, and individual factors in regulated contexts. *International Journal of Innovation Management*. https://doi.org/10.1142/S1363919621500158, 2150015.

Steinhauser, S., Doblinger, C., & Hüsig, S. (2020). The relative role of digital complementary assets and regulation in discontinuous telemedicine innovation in European Hospitals. *Journal of Management Information Systems, 37*(4), 1155–1183. https://doi.org/10.1080/07421222.2020.1831778.

Sun, L., Song, F., Shi, N., Liu, F., Li, S., Li, P., et al. (2020). Combination of four clinical indicators predicts the severe/critical symptom of patients infected COVID-19. *Journal of Clinical Virology, 128*, 104431. https://doi.org/10.1016/j.jcv.2020.104431.

Tanne, J. H., Hayasaki, E., Zastrow, M., Pulla, P., Smith, P., & Rada, A. G. (2020). Covid-19: How doctors and healthcare systems are tackling coronavirus worldwide. *BMJ (Clinical Research ed.), 368*, m1090. https://doi.org/10.1136/bmj.m1090.

Tsai, C.-h., Lin, C.-F., & Liu, H.-W. (2020). The diffusion of the sandbox approach to disruptive innovation and its limitations. *Cornell International Law Journal, 53*(3).

Venkatesh, V., Xiaojun, Z., & Sykes, T. A. (2011). "Doctors do too little technology": A longitudinal field study of an electronic healthcare system implementation. *Information Systems Research, 22*(3), 523–546. https://doi.org/10.1287/isre.1110.0383.

Whitehouse, D., & Marti, T. (2020). COVID-19: Defining a digital-first approach that adds value. *HealthManagement.org, 20*(4), 313–315.

Whitelaw, S., Mamas, M. A., Topol, E., & Van Spall, H. G. C. (2020). Applications of digital technology in COVID-19 pandemic planning and response. *The Lancet Digital Health, 2*(8), e435–e440. https://doi.org/10.1016/S2589-7500(20)30142-4.

World Health Organisation. (2020a). *Contact tracing in the context of COVID-19*. Retrieved from https://www.who.int/publications/i/item/contact-tracing-in-the-context-of-covid-19

World Health Organisation. (2020b, July 30). *Timeline of WHO's response to COVID-19*. Retrieved from https://www.who.int/news-room/detail/29-06-2020-covidtimeline

World Health Organization. (2010). *Telemedicine – Opportunities and developments in member states*. Retrieved.

Wu, J., Zhang, P., Zhang, L., Meng, W., Li, J., Tong, C., Li, S., et al. (2020). Rapid and accurate identification of COVID-19 infection through machine learning based on clinical available blood test results. *medRxiv*, 2020.2004.2002.20051136. https://doi.org/10.1101/2020.04.02.20051136