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What Disruptive Technologies Mean For New Healthcare Services

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ABSTRACT

The standard of medical care has risen as a result of the industry's rapid adoption of disruptive technology. When healthcare technologies are truly disruptive, they usher in new, more effective methods of diagnosing and caring for patients. This study investigates and examines the influence of technological transformation in healthcare innovation. We begin by evaluating existing and developing technologies in the context of healthcare service innovation. Then, we rely on the perspectives of key thought leaders from industry, consultancy, and clinical practice to forecast how digitalization will affect important components of the healthcare value chain, such as stakeholder relationships, service operations, resource needs, and healthcare economic systems.

Introduction

We investigate the role that digital disruption plays in the innovation of healthcare service. We conduct an analysis of the various aspects in which numerous occurrences of digital technology have the ability to reshape healthcare delivery, and we draw on the insights of leading experts from across industry, consultancy services, and healthcare delivery regarding how smart disruption can be anticipated to impact healthcare stakeholders, service operations, resources, and market mechanisms of healthcare [1-3].

Significant challenges are being posed to the healthcare systems of most countries by factors such as increasing populations, populations that are getting older, rising rates of chronic condition, the need to improve the accessibility to services for individuals in isolated places, and ever-higher expectations from consumers. These factors all contribute to an increase in the cost of providing healthcare, which in turn puts pressure on the budgets of both the public and private sectors. The ever-increasing price of technology is another obstacle to overcome; but, technology may, ironically, be a contributor to solutions that disrupt the conventional organizational framework of the healthcare sector as well as its business model [4]. It is hoped that such a transition would make it possible to provide treatment and preventative programs in a manner that is more efficient and effective, which may in turn lead to better health outcomes. In spite of the fact that genomics, nanomaterials, and digitization are all sorts of technology that are shaking up the sector, the latter, which combines software and hardware, will be the primary focus of this investigation.

Traditional industries have been and are being fundamentally altered as a result of a phenomena that emerged in the twenty-first century and is known as digital disruption. Mass communication, publishing, retailing, banking sectors, film and music allocation are some of the industries that have experienced the adoption of innovative revenue streams by new yet small and maneuverable firms that utilise emerging innovations to offer a more appealing value assertion than that which is provided by the incumbents in those industries. This is congruent with the more general idea of disruptive innovation, which describes "how difficult, costly goods and services are changed into simpler, inexpensive ones," with the added benefit of expanded accessibility.

In a similar vein, the process of digitization is starting to have an effect on all aspects of the value chain that make up the healthcare business, regardless of whether it operates in the government or the private sector. Hospitals, doctors, drug manufacturers, pharmacies, equipment manufacturers, diagnostic labs, insurers, and other businesses in the healthcare industry must adjust their business practices to the new surroundings in order to survive and thrive in the new environment. In order to offer an environment that is conducive to meeting the ever-evolving requirements of healthcare consumers, these adjustments should be complemented by corresponding changes to policy. While digitization has the potential to improve healthcare outcomes for all individuals, it also has the potential to exacerbate existing racial biases and inequalities in healthcare. Studies have shown that individuals from racial and ethnic minority groups often receive lower quality healthcare than their other counterparts, resulting in poorer health outcomes and higher rates of mortality [5]. This is due to a variety of factors, including implicit bias and discrimination among healthcare providers, limited access to healthcare services, and lower levels of health literacy among minority populations. As healthcare digitization becomes more widespread, it is important to ensure that these biases and inequalities are not perpetuated in the digital environment [6]. This can be achieved through targeted policies and initiatives aimed at promoting health equity and addressing the underlying causes of healthcare disparities.

It is required to evaluate how multiple sources of digital change may either separately manifest or converge to change the composition and organization of major functions in the medical value chain in order to foresee the impact that digital disruption will have on the healthcare industry. This is necessary in order to anticipate the effects that digital disruption will have on the healthcare industry[7]. Despite the fact that healthcare is a sector that is abundant in information, conventional models of healthcare are characterized by information imbalance. A genuine disruption should be a departure from the norm, and in the healthcare industry, this might be accomplished by redressing this imbalance via the collection and examination of data, which is made possible by technological advancements. To the degree that modernisation does not need governmental approvals, and with relatively affordable new technologies, the entry barriers for new competitors are being decreased. This implies that although opportunities and dangers remain common to sector participants, incumbents have to pay special attention to nimble new entrants prepared and prepared to disrupt since of lower levels of industry model risk [8].

The diagnosis and treatment of sickness and illness in people has been the primary emphasis of healthcare professions ever since they were first established. This primarily reactive form of care has virtually stayed constant for centuries, and it is characterized by a dispersed value chain that still has multiple interdependencies. This approach adds to wasteful duplication and possibly preventable clinical mistakes. However, the introduction and rapid growth of digital innovations since the middle of the twentieth century are having a profound effect on the healthcare industry. This can be seen in terms of enhanced research, improved delivery of care, and greater accessibility to both broad and specialized information by consumers. This, in turn, is driving more informed choice and so more efficient administration.

In addition to this, the proliferation of ICT is altering the conventional paradigm by making it possible to place a much higher focus on health promotion and disease prevention. According to the available evidence, the transition away from a model of healthcare that is driven by providers and institutions in the mass market has already begun. To a greater extent, consumers will be empowered by the innovation to take the current illness model and transform it into a model that is more consumer as well as personally driven, personalized wellness and protection model bringing enhanced autonomy over their own fitness as a supplement to the specialist advice offered by clinicians. It is quite expected that significant advantages, such as fewer instances of institutional care (like hospitalization for acute episodes of chronic conditions), would contribute to a decrease in both direct and indirect expenses.

There is a range of opinion about the specific manner in which digitization in particular, and innovation more generally, will propel the progression of the sector. The quick pace at which technological advancements continue to take place contributes significantly to the extent of this uncertainty. Studies suggest that one of the ways in which digitalization may generate disruptions is in the manner of decentralization. It will include taking the latest or even lesser versions of tech that is now found in hospitals and pushing it outside, to clinics, clinics, and ultimately to homes. This will be done in order to improve access to healthcare. Christensen believes that years of clinical practice will become more interchangeable in the future.

The amount of research and data that is accessible to physicians has grown in tandem with the advancements that have been made in technology. The transition from instinctive care to evidence-based healthcare and the subsequent development of personalized treatment has already been made by medical professionals. Payors, particularly those located in Europe (primarily the United Kingdom, France, and Germany), have been at the forefront of this movement and increasingly base payment on evidence-based results. It has become more difficult to get additional compensation for drugs that are unable to demonstrate that they are better effective, except for a few orphan pharmaceuticals. Treatment algorithms are able to become more clear and, as a result, simpler to teach when each new grade is added because to targeted gene-based medicines, which are an example of evidence-based medicine that is specifically focused. One could possibly ponder a future in which the succeeding phase of evidence-based care enables medical choices to be made based on phenotypes instead of genotypes. This development has the potential to make it possible for more aspects of patient care to be delegated to other parties, such as physician specialists, nurse practitioners, patients, and their families.

The ultimate result of digital disruption might be the production of increased certainty via timeliness, standardization, and evidence-based reasoning. This could be made possible by the growth in the amount of data that is now accessible. This becomes especially essential when it comes to providing a more precise characterization of patient outcomes and consequent adjustments to payment and reimbursement models. This transition is crucial for the healthcare sector, which is characterized by the convention of charging patients a charge for the services they get. Conventional business structures have been formed by this dynamic.

Since insurance companies (national as well as private) pay for services and products in the Australian healthcare system, the business-to-consumer (B2C) model that has emerged as a result is quite interesting. However, due to the fact that insurers pay for items and services, there has been little accountability on the part of providers (who decide what to buy and 'push' demand) and clients (who make consumer choices and 'pull' demand) up until recently. Since it offers more level of detail and conciseness to stakeholder anticipations across the chain, the possibilities to reinterpret value according to results rather than distinct services is significant. This is because it will fundamentally alter the conversation that takes place between providers, payers, and patients. Because of this shift in the accepted concept of value, the value proposition offered by healthcare providers will need to be revised, as will the metrics used to evaluate their level of success.

In an advanced economy, the aggregate of customer demands for speed and transparency, data to impact evidence-based rationale rather than instinctive decision, and compensation for results rather than service may lead to a more globalized marketplace vulnerable to various regulation in market forces conveniences, with low need for government involvement except when it is required to manage population-based risk. In other words, a more liberalized market may result in natural regulation in both supply and demand efficiencies, with little necessity for government involvement other than where it is necessary to provide.

Definitions

The emergence of new terminology into the field of healthcare has been largely attributed to the advent of digitization. The word "telehealth," which incorporates the notions of "telemedicine" and "telecare," is the one that has gained the greatest popularity among these three. The defining attributes are indicative of use by health providers in many nations, despite the fact that there is no one meaning that is generally recognized for each of these phrases.

The United States Health Resources and Services Administration (HRSA) defines telehealth as "the use of digital documents and telecommunications innovations to endorse long range clinical health care, customer and specialist health-related training, public health as well as health administration." Telehealth involves medical services offered by telemedicine as well as non-clinical services in remote locations such as provider training, organizational meetings, and continuous professional training.

"the provision of healthcare services to patients in distant areas," is how the company Frontier Communications Corporation defines telemedicine. Examples of this include patient consultations with clinical professionals that take place through a video connection; the remote monitoring of a patient's vital signs; remote medical evaluations and diagnoses based on medical imaging that is digitally communicated; and the remote prescription of medication.

The term "telecare" denotes the utilization of technology that allows patients to get medical attention in the comfort of their own homes, obviating the need for them to be admitted to an institution. While the patient keeps their freedom in a setting that is comfortable for them, the healthcare system experiences a reduction in both costs and strain.

IT

Because digital technologies for information and communication are so diverse, intricate, and dependant on one another, it is imperative that a thorough examination of each technology and the possible role it might play in revolutionizing healthcare be carried out.

Apps/Software

The term "app" refers to a software program that can be downloaded into a mobile device. This application was designed to facilitate the performance of a certain task. Since 2007, the quantity of healthcare applications that have been created for doctors and consumers has significantly grown. This rise may be attributed, in large part, to the proliferation of mobile electronic devices such as cellphones, tablets, and smartwatches.

Apps that are designed to, among other things: monitor sleeping habits to aid in optimization of circadian rhythm; offer details to enhance nutrition and diet; monitor an individual's physical action in comparison to suggested standards; monitor chronic health conditions and alert users to unforeseen situations; test and enhance intellectual capabilities; enable remote diagnosis; evaluate basic health information; and transmit anomalies to health care providers for more thorough analysis are some examples.

The overarching goals of these types of applications are to reduce the risk of sickness developing, speed up therapeutic intervention, promote user convenience, and gather, combine, and analyze huge volumes of diverse data in order to dramatically improve the diagnostic capabilities of physicians.

High Speed Broadband

The architecture of the network that enables the transmission of information in the form of text, speech, and video between people, between organizations, and between systems is made possible by advances in communications technology, which is a fundamental facilitator of digital disruption. The most contemporary kind of communications technology is known as high speed broadband. It consists of a network of optical fiber, fiber cable, and/or mobile connections and enables the fast transfer of massive amounts of data in a safe, timely, and secure manner across geographic areas. It is feasible to achieve data transmission rates of up to 1 gigabit per second. Recent technology advancements have made it possible for broadband to operate at reasonably high rates, up to 100 Mb/s, across both traditional copper phone lines and satellite connections.

This technology functions as a platform for the transmission of diagnostic pictures and computerized patient data. In addition, the availability of patient care is enhanced, as is its efficiency in terms of both cost and expenditure, thanks to the increased mobility of data made possible by monitoring carried out using wireless devices.

As a result, the locations of healthcare training, diagnosis, and treatment are undergoing significant changes as a result of the proliferation of high-speed internet. A skilled surgeon or a learner based in a big city may, for instance, perform on a patient placed in a hospital in a regional area using high-speed internet in combination with high-resolution video and modern robots.

The players in the healthcare business are obligated to ensure the dependability and safety of data networks and information services as a result of the consequences. This requires the allotment of suitable quantities of capital investment as well as operational spendings in order to guarantee that the IT infrastructure will continue to be able to support high speed transmission rate while also guaranteeing that the most suitable and advanced safeguards will be in place to safeguard the data transfer process.

Wi-Fi

Wi-Fi is a communication system that relies on a network to function. It enables mobile connection between devices that are able to communicate with each other, hence increasing the adaptability and effectiveness of therapeutic services. The improvement of clinical processes is also made possible by the provision of wireless access to client data in real time. Good data transmission speeds, high levels of interoperability, and solid security features are some of the benefits that may be realized by using this technology, which currently has a significant installed base across the majority of business sectors. The ongoing development of Wi-Fi technology has resulted in improvements that enhance the user experience. These improvements include an increase in capacity and throughput capacity, an improvement in coverage, and a reduction in latency.

Injectors, smart mattresses, wireless EKGs, and oxygen monitoring systems are some examples of the kind of technological advancements that have been made available to medical professionals as a result of recent years' worth of research and development in the field of healthcare. These and other devices work in combination with mission-critical data solutions including such connectivity to eMRs as well as real-time accessibility to X-rays and MRI images, amongst other things. The provision of clinical telepresence via the use of wireless internet connections helps to increase the accessibility of high-quality medical treatment in rural locations.

eMRs

Individual healthcare practitioners have historically been responsible for the maintenance of patient records in a hard copy format. The fragmented manner in which these documents are kept in storage makes it impossible to form a linked, comprehensive, and longitudinal understanding of the patient's medical history. Electronic medical records, on the other hand, are stored in a digital format, which makes it possible for relevant providers to have rapid and secure access to real-time patient data. These electronic records are able to offer a patient's complete medical history, including diagnoses of diseases, information of immunizations, allergies, prescription drugs, treatment plans, and radiology as well as laboratory test findings.

Electronic medical records, in contrast to paper records, have the potential to enhance patient outcomes by providing a number of advantages. These benefits include: • A more comprehensive perspective of a patient's treatment, which leads to better decision-making by physicians. • The ability to rapidly and readily communicate information with numerous healthcare practitioners who are engaged in the treatment of a patient • More accurate diagnosis and therapy that is more successful overall. • The automation of workflows and the streamlining of procedures across the whole of the medical value chain, which led to increased efficiency and larger cost savings as a consequence.

In addition to the advantages that are individual to the patient, having access to electronic copies of aggregated patient information makes it easier for providers to do aggregate analyses of patient groups, which in turn enables providers to perform comparative evaluations of outcomes. Because of this, such information may be helpful in deriving value and therefore obtaining payment from payers. However, there is a significant amount of regulation about privacy that has to be addressed with before we can fully realize the possibilities of this notion. Additionally, national regulations make it impossible to store data using a cloud computing strategy, and many different jurisdictions do not let the data of its citizens to be kept outside of the country.

Big Data and Data Analytics

Big data may be broken down into five distinct yet interconnected categories: 1. The quantity of the data with regard to its administration and storage is referred to as its volume. 2. The term "variety" refers to both the structure and the many kinds of data. 3. The rate at which data are created, processed, and evaluated is referred to as the velocity of these activities. 4. The quality of the data, its relevance, its forecasting capacity, and its significance are all aspects of veracity. 5. The value of the data is the advantage that is obtained by people who use the data.

The role of data analytics in OR (Operating Room) efficiency is becoming increasingly significant. Information from data analytics can be used to identify areas of improvement and optimize various aspects of OR operations, such as scheduling, resource allocation, and patient flow. According to a study by Trivedi & Patel (2021a) improving operating room efficiency has a substantial impact on cost savings, patient satisfaction, and surgical department morale [39]. By analyzing data related to patient flow, OR utilization, and surgeon productivity, hospitals can identify areas of inefficiency and make data-driven decisions to improve OR operations. Furthermore, data analytics can also assist in predicting patient demand, which can help hospitals manage resources more effectively. By using predictive analytics, hospitals can estimate the number of patients that will require surgery on a given day and allocate resources accordingly. This can help reduce wait times and increase OR utilization, ultimately leading to improved efficiency.

It is very necessary to manage the data sources, the content, the consistency, the access and the security, the stewardship, and the user training in order to keep the data integrity intact. It is possible for problems to arise with the data's unreliability, inaccessibility, inaccuracy, or omission if there is insufficient management. The term "data analytics" refers to the process of analyzing huge amounts of data that come from a variety of sources, as well as the simplicity and rapidity with which the study may be carried out. The information included in electronic health records is closely intertwined with big data and the analysis of this data.

Big data as well as data insights have a lot of potential uses in the medical field, and these uses span across a large variety of fields. There are four main types of application:

1. The management of the distribution of healthcare and the expenditures connected with it is referred to as "administration and delivery." 2. Helping clinicians with their decision-making is the purpose of clinical decision support. 3. The phrase "clinical information" refers to the information collections that are made accessible expressly for the purpose of data analytics. 4. Analysis of people and groups, including their habits and ways of life, in terms of demographics, with a focus on behavior and consumption.

Cognitive Computing and Artificial Intelligence

The capacity of a computer or other device to integrate learning into its own programming is referred to as cognitive computing. It is a subset of AI that makes an effort to simulate the way in which people think, particularly in regards to perception, understanding, and reasoning. By gaining access to large amounts of data, the goal is to answer complicated issues that include a large number of undefined variables.

In most cases, the software that serves as the basis for cognition computing and ai technologies calls for computer hardware that is endowed with robust data processing capabilities. Predicting the behavior of the stock market and the weather are two examples of applications that have been developed so farAI can be used to analyze large amounts of patient data and identify patterns and trends that can inform clinical decision-making. This can help healthcare providers to personalize treatment plans and improve patient outcomes. AI can also be used to automate routine tasks such as scheduling appointments and processing paperwork, freeing up healthcare providers to focus on patient care. In the field of medicine, the capabilities of modeling and simulation offered by the technology have a broad range of applications that may help improve patient outcomes.

In addition to improving patient outcomes, AI can also increase hospital efficiency by streamlining administrative tasks and reducing costs. For example, AI-powered systems can optimize hospital workflows by predicting patient volumes, identifying bottlenecks in the system, and reallocating resources accordingly. This can help to reduce wait times, increase the efficiency of care delivery, and ultimately improve patient satisfaction. AI can also be used to monitor patient outcomes and identify areas where improvements can be made, allowing healthcare providers to continuously improve the quality of care they provide. For instance, with Random Forest regression, Trivedi & Patel (2020) found that integration of AI and ML is reportedly essential to reduce the length of time that patients must wait [54]. The field of oncology particularly is an area of application in which accelerated modeling approaches may be used to make more precise predictions about the course of development of certain tumors. This is currently leading to enhanced diagnosis and treatment by physicians, but additional considerable improvements are expected to occur in the near future as the software continues to grow more intelligent and the hardware continues to become ever more sophisticated.

Perspectives

Considering that the industry is highly fragmented while also being closely intertwined through interdependencies, the complexity that results means that those who are most adequately placed to comprehend the extent and scale of such disruption are either those who are in charge of making decisions for healthcare institutions or those who have a vested the company’s interest of healthcare. Discussions with key thought leaders, such as the chief executive officer of a global private clinic group with over 200 hospitals located in 5 different nations, a top executive from a worldwide health consulting business, and a qualified healthcare executive who already has held clinical and organizational knowledge in university, healthcare, and consulting organizations provided valuable insights. These findings have been categorized according to four primary settings, which are as follows: (1) stakeholders, particularly patient outcomes; (2) service activities; (3) resources; and (4) healthcare market mechanisms.

Stakeholders

The most significant source of change for stakeholders will be to the manner in which care is provided, with an increased emphasis on the experience provided to customers.

Consumers increasingly anticipate that the health care and social services systems will become more responsive to the specific requirements of people, and this expectation is growing. Customers anticipate that their autonomous right to have a part in the decision of their treatment will be honored, as opposed to being treated like a number inside a system, which is their primary expectation. As a client in a hospital, for instance, he/she get to decide what he/she want to consume and when wants to eat it. As a result of the fact that healthcare facilities, such as hospitals, are highly integrated ecosystems in which the connectivity between nodes generates rigidity rather than flexibility, it is not always possible to guarantee compliance with patient preferences, even for seemingly straightforward requests. This is because of connections with other standardized processes and procedures, such as the accessibility of nursing personnel to help with feeding, the mass manufacture of meals, and logistics operating to tight schedules to serve huge numbers of patients. This list is not exhaustive. It is possible to state that despite the fact that technological advancements have made it possible for greater adaptability in meal preferences (albeit at the expense of additional expense), such ability to adapt is likely to be more pervasive in hospitals because choice is at the center of the value proposition offered by private healthcare.

The advantage of meeting the desire for enhanced openness and accessibility to data in the healthcare industry is that it results in a customer and payer that is better informed. Although the technology infrastructure to facilitate data collecting and openness already exists, suitable and scalable reporting methods have not yet been implemented. For instance, it is difficult to locate information that determines the choice of surgeons, such as the typical duration of stay for a certain treatment, the percentage of patients who required unexpected readmission, and the infection rate. Further discourse on the changes in policy and regulation, as well as the legal considerations that are necessary to bring about this dynamic, is warranted in order to meet the demand for this knowledge that has been expressed by stakeholders.

In spite of the fact that technologies of the next generation, such as nano, tailored medicines, and genetic screening, have great potential, there has not been a stepwise rise in the rate of advancement. On a more global scale, instances of this include the slow but steady increase in the average life expectancy, as well as the fact that there is still no known treatment for cancer. Consequently, even though the whole of the human genome has indeed been sequenced, the influence on healthcare in the form of a major disruption to the trends in healthcare has not yet materialized.

Activities/operations

The invention of penicillin, the breakthrough of antipsychotics, breakthroughs in surgical techniques that made it possible to perform open-heart surgery, joint replacement, and kidney transplantation, and the discovery that bacteria are the cause of peptic ulceration are all examples of the incremental changes that have gradually brought about a revolution in medical care over the course of history. Despite the exponential growth of technology, which is being manifested via widespread digitization, there are specific aspects of the healthcare business that may restrict the consequences of the same magnitude. These characteristics might include:

The protective impact of regulation on industry suppliers offers some degree of cushioning against widespread upheaval, and the complexity of regulatory demands seems to expand every year in keeping with the assumption that volatility will be regulated to zero if at all feasible. The challenge of where and how to give coordinated care in a safe manner is essentially a reflection of the complicated nature of care, and this accounts for the majority of the question. For instance, there are alternatives to hospital treatments that are on the simpler end of the complexity spectrum, such as gastroenterological interventions; these tasks may be performed at scale by day surgeries. Even still, extrapolating this tendency to settings other than day surgery is very improbable due to the regulatory restrictions that exist across the healthcare industry as a whole and the assumption that patient safety is a responsibility that must not be sacrificed.

Resources

While checking for potentially disruptive effects on formal services, it is challenging to foresee a technology-based substitute to the services provided by humans, who make up the majority of the resources. Because the overwhelming bulk of services offered by hospitals are carried out by people, the hospitals' primary lines of business should continue to operate normally for the coming years. Since there is currently no viable alternative to the nuances of social interaction and empathy, this situation is likely to continue for some time. The resource basis ought to buffer the healthcare industry from role replacement and basic service disruption, unless fast advancements in artificial intelligence led to machines that can successfully replace the complexities of human comprehension and interaction.

The advancement of technology in certain resource sectors does not always connect to the advancement of healthcare in general. The decision made by certain hospitals to forego digitalization in the domain of eMRs is rational when seen from the point of view of risk management as well as economics. Despite the fact that electronic records are touted to improve accuracy and decrease the likelihood of errors, they are not risk-free. Concerning matters pertaining to the safety of data stored digitally, paper-based records are inherently resistant to the dangers posed by modern technology. In addition, the case for transitioning to electronic medical records is not compelling because there is presently no strong evidence on error prevention nor a decrease in the cost of error, and there is a correlating absence of data for significant enhancements in productive output. This is why the case for transitioning to electronic medical records is not compelling. A hospital that had only just been built to conform with the greatest degree of electronic medical record application offered an insight in which they contrasted the benefits of using electronic medical record technology to the paper-based benchmark. Because of the high expenses of implementing and pushing the technology across the hospital, it was concluded that the roi was relatively poor. This was due to the fact that there was no plainly detectable meaningful patient gain or cost advantage. In spite of this, the very existence of technology, despite the fact that it does not yet have a clear value proposition, is an indication of the possibility of a revolution in the service delivery model in the future. The field of artificial intelligence (AI) is rapidly expanding, with increasing applications across a range of industries including healthcare. However, the scarcity of skilled AI specialists has resulted in adoption delays. As Wang et al. (2021) and Trivedi & Patel (2021b) pointed out, there is a growing need for AI adoption across all industries, and healthcare providers are finding it increasingly difficult to launch AI-based initiatives due to a shortage of resources [78, 81]. This shortage of talent has caused a bottleneck in the industry, limiting the pace of innovation and the ability of healthcare providers to improve patient outcomes.

The lack of AI specialists is a major concern for healthcare providers as they face a wide range of challenges, from the need to analyze vast amounts of data to the development of complex algorithms that can support clinical decision-making. These tasks require highly specialized skills that are in short supply, and healthcare providers are struggling to find qualified personnel to fill these roles. As a result, many healthcare organizations are unable to develop and implement AI-based initiatives, which could improve patient care and outcomes. The scarcity of skilled AI specialists is thus a major obstacle to the widespread adoption of AI in healthcare, and it is a challenge that must be addressed if the industry is to realize the full potential of this transformative technology. In the field of radiology, for instance, the possibility of a computer-aided diagnosis is quite real and is made possible by algorithms that make it possible to analyze a number of different pictures. Another industry that has been affected by digital disruption is pathology. Assays have been automated, which has resulted in a decreased requirement for human resources. In both cases, the technology in question is 66 G. Because to the work done by Ford et al., it is now possible for these solutions to be provided on a large scale and remotely, which has resulted to increased productivity and decreased expenses.

Although there may be chances to boost efficiency in many aspects of the value chain, the human interaction of treatment cannot be digitalized away completely. However, there may be opportunities to do so. The degree to which person participating in the evaluation is required for the provision of care will determine the scope of the impact that digital disruption will have on business delivery models. Sections in which a digital interface by now exists and is crucial to the actions conducted will be vulnerable to technological transformation.

Conclusion

According to prominent thought leaders in the For-Profit, Advisory, and Academic sectors, although new tech is implicitly implicated and will play a significant part in health care services disruption, it may not be the only driver of disruption to the fundamental structure of the healthcare system. The disruption will have an influence on stakeholder expectations, activity organization, resource use, and healthcare delivery economic models.

Technological advancements will reshape how certain aspects of healthcare are provided, resulting in cost reductions and efficiency via scale, such as radiography and pathology services. The community's omnipresent need for healthcare, labor-intensive resource limits, inherent significant risk in health services, and the consequent necessity for wide regulation all help to defend against fundamental change.

The data created, recorded, and analyzed as a result of healthcare digitisation will help to change the composition and organization of important operations in the medical value chain. The potential of this data to deliver greater detail and clarity to all stakeholders will transform expectations throughout the value chain, radically altering the discourse between providers, payers, policymakers, and patients. As a consequence, rather than the skewed motivations established by traditional fee-for-service arrangements, a more liberalized market subject to natural management in market forces efficiency might develop.

Despite this, among the most challenging difficulties for creators and suppliers of digitized services is determining how to properly monetize them. Unfortunately, numerous digital practices, including free and freemium offerings, have impacted customers' relationships with digital technology, especially their desire to pay. Many consumers expect the advantages of digitization without hesitation, either tacitly or openly. While providing such services has helped businesses distinguish themselves and increase market share, it has been at the expense of profitability. As a result of diminishing economic incentives, the change to digitization may lag significantly after an initial surge of offers.

Digitization will impact and facilitate industry-wide change, but the ultimate disruptor will be a shift in the social and political terms and conditions that characterizes the healthcare system, driven by the need to transition from volume-driven fee-for-service concepts to more cost effective, evidence-based payment models based on results. Existing therapeutic care models and accompanying commercial structures will undergo modifications as a result of digitization. This will give motivation for innovation, the development of new income sources, and the establishment of new cost structures, all of which will eventually alter healthcare delivery to suit the demands of people and redefined metrics of value.

References

[1] Intas G, Kapsabelis M, Stergiannis P, Platis C, Pierrakos G. Assessment of healthcare professionals' knowledge and awareness on aspects related to ionizing radiation examinations in Athens, Greece. Adv Exp Med Biol 2021;1337:185–93. https://doi.org/10.1007/978-3-030-78771-4_21.

[2] Stefanatou P, Xenaki L-A, Karagiorgas I, Ntigrintaki A-A, Giannouli E, Malogiannis IA, et al. Fear of COVID-19 impact on professional quality of life among mental health workers. Int J Environ Res Public Health 2022;19:9949. https://doi.org/10.3390/ijerph19169949.

[3] Goldstone LW. Unmet medical needs and other challenges in the treatment of patients with schizophrenia. Am J Manag Care 2020;26:S48–54. https://doi.org/10.37765/ajmc.2020.43011.

[4] Horwood J, Cabral C, Hay AD, Ingram J. Primary care clinician antibiotic prescribing decisions in consultations for children with RTIs: a qualitative interview study. Br J Gen Pract 2016;66:e207-13. https://doi.org/10.3399/bjgp16X683821.

[5] Song Z, Johnston RM, Ng CP. Equitable Healthcare Access During the Pandemic: The Impact of Digital Divide and Other SocioDemographic and Systemic Factors. Applied Research in Artificial Intelligence and Cloud Computing 2021;4:19–33.

[6] Song Z, Mellon G, Shen Z. Relationship between Racial Bias Exposure, Financial Literacy, and Entrepreneurial Intention: An Empirical Investigation. Journal of Artificial Intelligence and Machine Learning in Management 2020;4:42–55.

[7] Dahlweid M, Rausch D, Hinske C, Darmoni S, Grosjean J, Santi J, et al. Clinical Knowledge Platform (CKP): A collaborative ecosystem to share interoperable clinical forms, viewers, and order sets with various EMRs. Stud Health Technol Inform 2022;298:117–21. https://doi.org/10.3233/SHTI220919.

[8] Zhao Q, Li J, Zhao L, Zhu Z. Knowledge guided feature aggregation for the prediction of chronic obstructive pulmonary disease with Chinese EMRs. IEEE/ACM Trans Comput Biol Bioinform 2022;PP:1–10. https://doi.org/10.1109/TCBB.2022.3198798.

[9] Yang C, Xiao D, Luo Y, Li B, Zhao X, Zhang H. A hybrid method based on semi-supervised learning for relation extraction in Chinese EMRs. BMC Med Inform Decis Mak 2022;22:169. https://doi.org/10.1186/s12911-022-01908-4.

[10] Weichenthal M, Svane IM, Kandolf Sekulovic L, Mangana J, Mohr P, Marquez-Rodas I, et al. EMRseq: Registry-based outcome analysis on 1,000 patients with BRAF V600–mutated metastatic melanoma in Europe treated with either immune checkpoint or BRAF-/MEK inhibition. J Clin Oncol 2022;40:9540–9540. https://doi.org/10.1200/jco.2022.40.16_suppl.9540.

[11] Chen X, Xu S, Qin T, Cui Y, Gao S, Kong W. AQ–ABS: Anti-quantum attribute-based signature for EMRs sharing with blockchain. 2022 IEEE Wireless Communications and Networking Conference (WCNC), IEEE; 2022. https://doi.org/10.1109/wcnc51071.2022.9771830.

[12] Yang C, Xiao D, Luo Y, Li B, Zhao X, Zhang H. A hybrid method based on semi-supervised learning for relation extraction in Chinese EMRs. Research Square 2022. https://doi.org/10.21203/rs.3.rs-1357125/v1.
[13] Silva V, Ribeiro J, Rocha J, Manaia CM, Silva A, Pereira JE, et al. High frequency of the EMRSA-15 clone (ST22-MRSA-IV) in hospital wastewater. Microorganisms 2022;10:147. https://doi.org/10.3390/microorganisms10010147.
[14] Hamzah AMC, Al-Trad E, Puah SM, Rahman NIA, Ismail S, Yeo CC, et al. Whole genome sequence analysis of methicillin-resistant Staphylococcus aureus indicates predominance of the EMRSA-15 (ST22-SCCmec IV[2b]) clone in Terengganu, Malaysia. Int J Antimicrob Agents 2021;58:21004039. https://doi.org/10.1016/j.ijantimicag.2021.106421.132.
[15] Saberi MA, Adda M, Mcheick H. Towards an ABAC Break-Glass to access EMRs in case of emergency based on Blockchain. 2021 IEEE International Conference on Digital Health (ICDH), IEEE; 2021. https://doi.org/10.1109/icdh52753.2021.00041.
[16] Zhai P, Wang C, Fang Y. LSLSD: Fusion long short-level semantic dependency of Chinese EMRs for event extraction. Appl Sci (Basel) 2021;11:7237. https://doi.org/10.3390/app11167237.
[17] Zhang K, Hu B, Zhao X, Song Y, Zhuang L, Zan H. A HIE-BERT model for diagnosis assistant based on Chinese obstetric EMRs. 2021 IEEE 9th International Conference on Healthcare Informatics (ICHI), IEEE; 2021. https://doi.org/10.1109/ichi52183.2021.00084.
[18] Yang C. A hybrid method based on semi-supervised learning for relation extraction in Chinese EMRs (preprint). JMIR Preprints 2021. https://doi.org/10.2196/preprints.28220.
[19] Lin W, Tian X, Lu X, Ma D, Wu Y, Hong J, et al. Prediction of bedridden duration of hospitalized patients by machine learning based on EMRs at admission. Comput Inform Nurs 2021;40:251–7. https://doi.org/10.1097/CIN.0000000000000765.
[20] Zhao R, Wang L, Liu Y, Shao M, Yang W, Fu Y, et al. The influence of adjunctive traditional Chinese medicine therapy on survival in primary liver cancer: A real-world study based on EMRs. Research Square 2021. https://doi.org/10.21203/rs.3.rs-505666/v1.
[21] Li C, Dong M, Li J, Xu G, Chen X, Ota K. Healthchain: Secure EMRs management and trading in distributed healthcare service system. IEEE Internet Things J 2021;8:7192–202. https://doi.org/10.1109/jiot.2020.3038721.
[22] Tam CS, Gullick J, Saavedra A, Vernon ST, Figtree GA, Chow CK, et al. Combining structured and unstructured data in EMRs to create clinically-defined EMR-derived cohorts. BMC Med Inform Decis Mak 2021;21:91. https://doi.org/10.1186/s12911-021-01441-w.
[23] Gao Y, Fu X, Liu X, Zhou K, Wu J. SMP-graph: Structure-enhanced unsupervised semantic graph representation for precise medical procedure coding on EMRs. 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), IEEE; 2021. https://doi.org/10.1109/bibm52615.2021.9669522.
[24] Durbin SM. 2019 Spring Meeting of the EMRS, Symposium E: Earth-abundant next generation materials for solar energy - III. Mater Sci Semicond Process 2021;121:105407. https://doi.org/10.1016/j.mssp.2020.105407.
[25] M MK V, Sastry NKB, Moonesar IA, Rao A. Predicting universal healthcare through health financial management for sustainable development in BRICS, GCC, and AUKUS economic blocks. Front Artif Intell 2022;5:887225. https://doi.org/10.3389/frai.2022.887225.
[26] Tucci V, Saary J, Doyle TE. Factors influencing trust in medical artificial intelligence for healthcare professionals: a narrative review. J Med Artif Intell 2022;5:4–4. https://doi.org/10.21037/jmai-21-25.
[27] Chen T, Carter J, Mahmud, Khuman AS, editors. Artificial intelligence in healthcare. 1st ed. Singapore, Singapore: Springer; 2022.
[28] Das S, Sanyal MK. Artificial Intelligence in Healthcare. LAP Lambert Academic Publishing; 2020.
[29] Nordlinger B, Villani C, Rus D, editors. Healthcare and Artificial Intelligence. 1st ed. Cham, Switzerland: Springer Nature; 2020. https://doi.org/10.1007/978-3-030-32161-1.
[30] Gunatilleke J. Artificial Intelligence in Healthcare. N. Janak Gunatilleke; 2022.

[31] Suen S-C, Scheinker D, Enns E, editors. Artificial intelligence for healthcare. Cambridge, England: Cambridge University Press; 2022. https://doi.org/10.1017/9781108872188.
[32] Lim C-P, Vaidya A, Jain K, Mahorkar VU, Jain LC, editors. Handbook of artificial intelligence in healthcare. Cham, Switzerland: Springer Nature; 2022. https://doi.org/10.1007/978-3-030-79161-2.
[33] Bhoi AK, Mallick PK, Mohanty MN, de Albuquerque VHC, editors. Hybrid Artificial Intelligence and IoT in Healthcare. 1st ed. Singapore, Singapore: Springer; 2022.
[34] Lim C-P, Chen Y-W, Vaidya A, Mahorkar C, Jain LC, editors. Handbook of artificial intelligence in healthcare. 1st ed. Cham, Switzerland: Springer Nature; 2021. https://doi.org/10.1007/978-3-030-83620-7.
[35] Parah SA, Rashid M, Varadarajan V, editors. Artificial Intelligence for Innovative Healthcare Informatics. 1st ed. Cham, Switzerland: Springer Nature; 2022. https://doi.org/10.1007/978-3-030-96569-3.
[36] Davenport T, Glaser J, Gardner E. Advanced introduction to artificial intelligence in healthcare. Cheltenham, England: Edward Elgar Publishing; 2022.
[37] Mahajan PS. Artificial intelligence in healthcare. Medmantra; 2021.
[38] Geisler E, Heller O, editors. Managing Technology in Healthcare. 1996th ed. Dordrecht, Netherlands: Springer; 2012.
[39] Trivedi S, Patel N. Optimizing OR Efficiency through Surgical Case Forecasting with ARIMA Averaging. ACST 2021;1:7–17.
[40] Spekowius G, Wendler T, editors. Advances in healthcare technology. 2006th ed. New York, NY: Springer; 2006. https://doi.org/10.1007/1-4020-4384-8.
[41] Spekowius G, Wendler T, editors. Advances in healthcare technology. Dordrecht, Netherlands: Springer; 2010.
[42] Zielinski K, Duplaga M, Ingram D, Zieli?ski K. Information Technology Solutions for Healthcare. London, England: Springer; 2006.
[43] Pandit UK, Alderweireldt FC, editors. Bioorganic Chemistry in Healthcare and Technology. New York, NY: Springer; 2012. https://doi.org/10.1007/978-1-4684-1354-0.
[44] Bottani E, Bellini V, Mordonini M, Pellegrino M, Lombardo G, Franchi B, et al. Internet of things and artificial intelligence for perioperative tracking patients: Towards a new model for an operating rooms. Research Square 2022. https://doi.org/10.21203/rs.3.rs-1929671/v1.
[45] Jana S, Sutton M, Mollayeva T, Chan V, Colantonio A, Escobar MD. Application of multiple testing procedures for identifying relevant comorbidities, from a large set, in traumatic brain injury for research applications utilizing big health-administrative data. Front Big Data 2022;5:793606. https://doi.org/10.3389/fdata.2022.793606.
[46] Milne R, Sheehan M, Barnes B, Kapper J, Lea N, N'Dow J, et al. A concentric circles view of health data relations facilitates understanding of sociotechnical challenges for learning health systems and the role of federated data networks. Front Big Data 2022;5:945739. https://doi.org/10.3389/fdata.2022.945739.
[47] Plough AL. Charting an equity-centered public health data system. Big Data 2022;10:S1–2. https://doi.org/10.1089/big.2022.0203.
[48] Chandra A, Martin LT, Acosta JD, Nelson C, Yeung D, Qureshi N, et al. Equity as a guiding principle for the public health data system. Big Data 2022;10:S3–8. https://doi.org/10.1089/big.2022.0204.
[49] Hassani H, Huang X, MacFeely S. Impactful digital twin in the healthcare revolution. Big Data Cogn Comput 2022;6:83. https://doi.org/10.3390/bdcc6030083.
[50] Martin LT, Chandra A, Nelson C, Yeung D, Acosta JD, Qureshi N, et al. Technology and data implications for the public health workforce. Big Data 2022;10:S25–9. https://doi.org/10.1089/big.2022.0208.
[51] Martin LT, Nelson C, Yeung D, Acosta JD, Qureshi N, Blagg T, et al. The issues of interoperability and data connectedness for public health. Big Data 2022;10:S19–24. https://doi.org/10.1089/big.2022.0207.

[52] Acosta JD, Chandra A, Yeung D, Nelson C, Qureshi N, Blagg T, et al. What data should be included in a modern public health data system. Big Data 2022;10:S9–14. https://doi.org/10.1089/big.2022.0205.
[53] Greer ML, Zayas CE, Bhattacharyya S. Repeatable enhancement of healthcare data with social determinants of health. Front Big Data 2022;5:894598. https://doi.org/10.3389/fdata.2022.894598.
[54] Trivedi S, Patel N. The Impact of Artificial Intelligence Integration on Minimizing Patient Wait Time in Hospitals. EQME 2020;3:21–35.
[55] Ding J, Errapotu SM, Guo Y, Zhang H, Yuan D, Pan M. Private empirical risk minimization with analytic Gaussian mechanism for healthcare system. IEEE Trans Big Data 2022;8:1107–17. https://doi.org/10.1109/tbdata.2020.2997732.
[56] Kumari S, Bhatia M, Stea G. Fog-computing based healthcare framework for predicting encephalitis outbreak. Big Data Res 2022;29:100330. https://doi.org/10.1016/j.bdr.2022.100330.
[57] Finnegan A, Potenziani DD, Karutu C, Wanyana I, Matsiko N, Elahi C, et al. Deploying machine learning with messy, real world data in low- and middle-income countries: Developing a global health use case. Front Big Data 2022;5:553673. https://doi.org/10.3389/fdata.2022.553673.
[58] Siriborvornratanakul T. Human behavior in image-based Road Health Inspection Systems despite the emerging AutoML. J Big Data 2022;9:96. https://doi.org/10.1186/s40537-022-00646-8.
[59] Rutjes H, Willemsen MC, Feijt MA, IJsselsteijn WA. The influence of personal health data on the health coaching process. Front Big Data 2022;5:678061. https://doi.org/10.3389/fdata.2022.678061.
[60] Call for papers: Special issue on artificial intelligence powered Internet of Healthcare Things (IoHT): Data science, emerging trends and applications. Big Data Min Anal 2022;5:161–161. https://doi.org/10.26599/bdma.2021.9020029.
[61] Esposito S, Orlandi S, Magnacca S, De Curtis A, Gialluisi A, Iacoviello L, et al. Clinical network for big data and personalized health: Study protocol and preliminary results. Int J Environ Res Public Health 2022;19. https://doi.org/10.3390/ijerph19116365.
[62] Garett R, Young SD. Ethical views on sharing digital data for public health surveillance: Analysis of survey data among patients. Front Big Data 2022;5:871236. https://doi.org/10.3389/fdata.2022.871236.
[63] Almagrabi AO, Ali R, Alghazzawi D, AlBarakati A, Khurshaid T. A reinforcement learning-based framework for crowdsourcing in massive health care internet of things. Big Data 2022;10:161–70. https://doi.org/10.1089/big.2021.0058.
[64] Olatunji IE, Rauch J, Katzensteiner M, Khosla M. A review of anonymization for healthcare data. Big Data 2022. https://doi.org/10.1089/big.2021.0169.
[65] Nguyen QC, Belnap T, Dwivedi P, Deligani AHN, Kumar A, Li D, et al. Google Street View images as predictors of patient health outcomes, 2017-2019. Big Data Cogn Comput 2022;6:15. https://doi.org/10.3390/bdcc6010015.
[66] Shakyawar SK, Sethi S, Southekal S, Mishra NK, Guda C. Big data analytics for modeling COVID-19 and comorbidities: An unmet need. Computational Intelligence Techniques for Combating COVID-19, Springer; 2021, p. 185–201. https://doi.org/10.1007/978-3-030-68936-0_10.
[67] Javaid M, Haleem A, Singh RP, Rab S, Suman R, Khan IH. Evolutionary trends in progressive cloud computing based healthcare: Ideas, enablers, and barriers. International Journal of Cognitive Computing in Engineering 2022;3:124–35. https://doi.org/10.1016/j.ijcce.2022.06.001.
[68] Supriya, Chattu VK. A review of artificial intelligence, big data, and blockchain technology applications in medicine and global health. Big Data Cogn Comput 2021;5:41. https://doi.org/10.3390/bdcc5030041.
[69] Sermet Y, Demir I. A semantic web framework for automated smart assistants: A case study for public health. Big Data Cogn Comput 2021;5:57. https://doi.org/10.3390/bdcc5040057.

[70] Kollias K, Xenaki L-A, Vlachos I, Dimitrakopoulos S, Kosteletos I, Nianiakas N, et al. The development of the Early Intervention in Psychosis (EIP) outpatient unit of Eginition University Hospital into an EIP Network. Psychiatrike 2020;31:177–82. https://doi.org/10.22365/jpsych.2020.312.177.
[71] Tran VP, Al-Jumaily AA, Islam SMS. Doppler radar-based non-contact health monitoring for obstructive sleep apnea diagnosis: A comprehensive review. Big Data Cogn Comput 2019;3:3. https://doi.org/10.3390/bdcc3010003.
[72] Chattu VK, Nanda A, Chattu SK, Kadri SM, Knight AW. The emerging role of blockchain technology applications in routine disease surveillance systems to strengthen global health security. Big Data Cogn Comput 2019;3:25. https://doi.org/10.3390/bdcc3020025.
[73] Singh J, Hamid MA. Cognitive computing in mental healthcare: A review of methods and technologies for detection of mental disorders. Cognit Comput 2022. https://doi.org/10.1007/s12559-022-10042-2.
[74] Bertini F, Allevi D, Lutero G, Montesi D, Calzà L. Automatic speech classifier for mild cognitive impairment and early dementia. ACM Trans Comput Healthcare 2022;3:1–11. https://doi.org/10.1145/3469089.
[75] Zhang Y, Chen Y, Yang W, Yu H, Lv Z. Human-centered intelligent healthcare: explore how to apply AI to assess cognitive health. CCF Trans Pervasive Comp Interact 2022;4:189–206. https://doi.org/10.1007/s42486-022-00102-9.
[76] Zhang Y, Ma H, Lv X, Han Q. Multimodal MRI analysis of brain metabolism in maintenance hemodialysis patients based on cognitive computing. J Healthc Eng 2021;2021:7231658. https://doi.org/10.1155/2021/7231658.
[77] Bandari V. Proactive Fault Tolerance Through Cloud Failure Prediction Using Machine Learning. ResearchBerg Review of Science and Technology 2020;3:51–65.
[78] Varun M, Annadurai C. RETRACTED ARTICLE: PALM-CSS: a high accuracy and intelligent machine learning based cooperative spectrum sensing methodology in cognitive health care networks. J Ambient Intell Humaniz Comput 2021;12:4631–42. https://doi.org/10.1007/s12652-020-01859-6.
[79] Varun M, Annadurai C. Retraction Note to: PALM-CSS: a high accuracy and intelligent machine learning based cooperative spectrum sensing methodology in cognitive health care networks. J Ambient Intell Humaniz Comput 2022. https://doi.org/10.1007/s12652-022-04167-3.
[80] Wang W, Chen L, Xiong M, Wang Y. Accelerating AI Adoption with Responsible AI Signals and Employee Engagement Mechanisms in Health Care. Inf Syst Front 2021. https://doi.org/10.1007/s10796-021-10154-4.
[81] Trivedi S, Patel N. The Determinants of AI Adoption in Healthcare: Evidence from Voting and Stacking Classifiers. RRST 2021;1:69–83.
[82] Babroudi NEP, Sabri-Laghaie K, Ghoushchi NG. Re-evaluation of the healthcare service quality criteria for the Covid-19 pandemic: Z-number fuzzy cognitive map. Appl Soft Comput 2021;112:107775. https://doi.org/10.1016/j.asoc.2021.107775.
[83] Chen M, Yang J, Hao Y, Mao S, Hwang K. A 5G Cognitive System for Healthcare. Big Data Cogn Comput 2017;1:2. https://doi.org/10.3390/bdcc1010002.
[84] Chen M, Jiang S. Analysis and research on mental health of college students based on cognitive computing. Cogn Syst Res 2019;56:151–8. https://doi.org/10.1016/j.cogsys.2019.03.003.
[85] Panwar A, Bhatnagar V. A cognitive approach for blockchain-based cryptographic curve hash signature (BC-CCHS) technique to secure healthcare data in Data Lake. Soft Comput 2021:1–15. https://doi.org/10.1007/s00500-021-06513-7.
[86] Preum SM, Munir S, Ma M, Yasar MS, Stone DJ, Williams R, et al. A review of cognitive assistants for healthcare. ACM Comput Surv 2021;53:1–37. https://doi.org/10.1145/3419368.
[87] Yuen KKF. The Primitive Cognitive Network Process in healthcare and medical decision making: Comparisons with the Analytic Hierarchy Process. Appl Soft Comput 2014;14:109–19. https://doi.org/10.1016/j.asoc.2013.06.028.

[88] Kislay A, Singh P, Shankar A, Nayak SR, Bhoi AK. A review on internet of things in healthcare applications. Cognitive Informatics and Soft Computing, Singapore: Springer Nature Singapore; 2022, p. 387–94. https://doi.org/10.1007/978-981-16-8763-1_31.
[89] Marshall T, Champagne-Langabeer T, Castelli D, Hoelscher D. Cognitive computing and eScience in health and life science research: artificial intelligence and obesity intervention programs. Health Inf Sci Syst 2017;5:13. https://doi.org/10.1007/s13755-017-0030-0.
[90] Hu B, Zhang Z. Evaluation of Big Data Analytics and cognitive computing in smart health systems. J Commer Biotechnol 2022;27. https://doi.org/10.5912/jcb1088.
[91] Kosana V, Teeparthi K, Rana A ul HS. Cognitive technology for a personalized seizure predictive and healthcare analytic device. Cognitive and Soft Computing Techniques for the Analysis of Healthcare Data, Elsevier; 2022, p. 29–58. https://doi.org/10.1016/b978-0-323-85751-2.00012-8.
[92] Jin G. Intervention of population health management innovation on economy based on cognitive computing. Inf Process Manag 2022;59:102805. https://doi.org/10.1016/j.ipm.2021.102805.
[93] Nguyen KTP, Medjaher K, Tran DT. A review of artificial intelligence methods for engineering prognostics and health management with implementation guidelines. Artif Intell Rev 2022. https://doi.org/10.1007/s10462-022-10260-y.
[94] Couture J, Lin X. Image- and health indicator-based transfer learning hybridization for battery RUL prediction. Eng Appl Artif Intell 2022;114:105120. https://doi.org/10.1016/j.engappai.2022.105120.
[95] Rocchetta R, Gao Q, Mavroeidis D, Petkovic M. A robust model selection framework for fault detection and system health monitoring with limited failure examples: Heterogeneous data fusion and formal sensitivity bounds. Eng Appl Artif Intell 2022;114:105140. https://doi.org/10.1016/j.engappai.2022.105140.
[96] Omar N, Nazirun NN, Vijayam B, Wahab AA, Bahuri HA. Diabetes subtypes classification for personalized health care: A review. Artif Intell Rev 2022. https://doi.org/10.1007/s10462-022-10202-8.
[97] Bandari V. The Adoption Of Next Generation Computing Architectures: A Meta Learning On The Adoption Of Fog, Mobile Edge, Serverless, And SoftwareDefined Computing. Ssraml 2019;2:1–15.
[98] Loftus TJ, Shickel B, Balch JA, Tighe PJ, Abbott KL, Fazzone B, et al. Phenotype clustering in health care: A narrative review for clinicians. Front Artif Intell 2022;5:842306. https://doi.org/10.3389/frai.2022.842306.
[99] Koutroulis G, Mutlu B, Kern R. Constructing robust health indicators from complex engineered systems via anticausal learning. Eng Appl Artif Intell 2022;113:104926. https://doi.org/10.1016/j.engappai.2022.104926.
[100] Hu R, Zhang M, Meng X, Kang Z. Deep subdomain generalisation network for health monitoring of high-speed train brake pads. Eng Appl Artif Intell 2022;113:104896. https://doi.org/10.1016/j.engappai.2022.104896.
[101] Afanasieva N, Gordeeva K, Muskharina Y, Zastavna O, Shuppe L, Andreikova I. Neuropsychological factors and practical methods of maintaining mental health in special conditions. Brain (Bacau) 2022;13:130–51. https://doi.org/10.18662/brain/13.2/336.
[102] Caffo BS, D'Asaro FA, Garcez A, Raffinetti E. Editorial: Explainable artificial intelligence models and methods in finance and healthcare. Front Artif Intell 2022;5:970246. https://doi.org/10.3389/frai.2022.970246.
[103] Sahana, Thejashwini, Kamath V, Lahari Y, Mohanchandra K. Blockchain based framework for secure data sharing of medicine supply chain in health care system. International Journal of Artificial Intelligence 2022;9:32–28. https://doi.org/10.36079/lamintang.ijai-0901.358.
[104] von Ulmenstein U, Tretter M, Ehrlich DB, Lauppert von Peharnik C. Limiting medical certainties? Funding challenges for German and comparable public healthcare systems due to AI prediction and how to address them. Front Artif Intell 2022;5:913093. https://doi.org/10.3389/frai.2022.913093.

[105] Liu Z, Chen Y, Zhao Y, Yu H, Liu Y, Bao R, et al. Contribution-Aware Federated Learning for smart healthcare. Proc Conf AAAI Artif Intell 2022;36:12396–404. https://doi.org/10.1609/aaai.v36i11.21505.
[106] Haktanır E, Kahraman C. A novel picture fuzzy CRITIC & REGIME methodology: Wearable health technology application. Eng Appl Artif Intell 2022;113:104942. https://doi.org/10.1016/j.engappai.2022.104942.
[107] Hussein D, Bhat G, Doppa JR. Adaptive energy management for self-sustainable wearables in mobile health. Proc Conf AAAI Artif Intell 2022;36:11935–44. https://doi.org/10.1609/aaai.v36i11.21451.
[108] Anazodo UC, Adewole M, Dako F. AI for population and global health in radiology. Radiol Artif Intell 2022;4:e220107. https://doi.org/10.1148/ryai.220107.
[109] Chen H, Ghosh S, Fan G, Behari N, Biswas A, Williams M, et al. Using public data to predict demand for mobile health clinics. Proc Conf AAAI Artif Intell 2022;36:12461–7. https://doi.org/10.1609/aaai.v36i11.21513.
[110] Abdulkhaleq MT, Rashid TA, Alsadoon A, Hassan BA, Mohammadi M, Abdullah JM, et al. Harmony search: Current studies and uses on healthcare systems. Artif Intell Med 2022;131:102348. https://doi.org/10.1016/j.artmed.2022.102348.
[111] M S AR, Nirmala CR, Aljohani M, Sreenivasa BR. A novel technique for detecting sudden concept drift in healthcare data using multi-linear artificial intelligence techniques. Front Artif Intell 2022;5:950659. https://doi.org/10.3389/frai.2022.950659.
[112] Mate A, Madaan L, Taneja A, Madhiwalla N, Verma S, Singh G, et al. Field study in deploying Restless Multi-Armed Bandits: Assisting non-profits in improving maternal and child health. Proc Conf AAAI Artif Intell 2022;36:12017–25. https://doi.org/10.1609/aaai.v36i11.21460.
[113] Ramaswamy A, R Gowda N, Vikas H, Prabhu M, Sharma DK, Gowda PR, et al. It’s the data, stupid: Inflection point for Artificial Intelligence in Indian healthcare. Artif Intell Med 2022;128:102300. https://doi.org/10.1016/j.artmed.2022.102300.
[114] Kiseleva A, Kotzinos D, De Hert P. Transparency of AI in healthcare as a multilayered system of accountabilities: Between legal requirements and technical limitations. Front Artif Intell 2022;5:879603. https://doi.org/10.3389/frai.2022.879603.
[115] Nico N, Charibaldi N, Fauziah Y. Comparison of memetic algorithm and genetic algorithm on nurse picket scheduling at public health center. Int J Artif Intell Robot 2022;4:9–23. https://doi.org/10.25139/ijair.v4i1.4323.
[116] Niehaus S, Hartwig M, Rosen PH, Wischniewski S. An occupational safety and health perspective on human in control and AI. Front Artif Intell 2022;5:868382. https://doi.org/10.3389/frai.2022.868382.
[117] Fecho K, Ahalt SC, Knowles M, Krishnamurthy A, Leigh M, Morton K, et al. Leveraging open electronic health record data and environmental exposures data to derive insights into rare pulmonary disease. Front Artif Intell 2022;5:918888. https://doi.org/10.3389/frai.2022.918888.
[118] Hulsen T, Petkovic M, Varga OE, Jamuar SS. Editorial: AI in healthcare: From data to intelligence. Front Artif Intell 2022;5:909391. https://doi.org/10.3389/frai.2022.909391.
[119] Antoniou G, Papadakis E, Baryannis G. Mental health diagnosis: A case for explainable artificial intelligence. Int J Artif Intell Tools 2022;31. https://doi.org/10.1142/s0218213022410032.