A SYSTEMATIC LITERATURE REVIEW OF THE TRANSFORMATION OF HEALTHCARE BY THE FOURTH INDUSTRIAL REVOLUTION

by

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ABSTRACT

The aging population and lifestyle factors have contributed to increased cases of chronic diseases which increase medical costs for both patients and healthcare providers and affect the quality of medical care. The unequal distribution of medical resources between urban and rural areas has also increased medical costs as patients seek medical care in well-resourced hospitals located in big cities. I explored the nature and extent of digital transformation in healthcare with the aim to determine (1) the dominant applications of 4IR technologies in healthcare (2) the impact of disruptive technologies on the delivery of healthcare and (3) how the Covid-19 pandemic has accelerated digital transformation in healthcare.

The study used a Systematic Literature Review (SLR) to analyse a final set of 84 papers from three major databases that met the specific inclusion, exclusion, and quality assessment criteria. A mixed-methods approach using both quantitative and qualitative thematic analysis was used to analyse the papers. The quantitative analysis showed that the majority of papers used the qualitative research method, followed by quantitative, and the least number of articles used a mixed-methods approach. The qualitative analysis reflected three broad themes (1) 4IR technologies driving transformation in healthcare (2) digital transformation areas in healthcare and (3) the impact of digital transformation in healthcare.

The results showed that the first–generation 4IR technologies have not met the expected comparative transformation levels in healthcare and the next generation technologies have more potential for increased transformation in healthcare. Specifically, the results showed that (1) healthcare is transformed from conventional, centralised and reactive to digital, distributed, networked and proactive personalised care system for remote health monitoring, diagnostics and treatment at the point of care (2) the leading technologies transforming healthcare are IoT, AI and Big data (3) the main areas of transformation in healthcare are personalised care, precision medicine, telemedicine, remote health monitoring, data management, and clinical decision support including improved diagnostic and treatment outcomes (4) the impact of the transformation is observed through improved quality of medical care, reduced medical costs, and improved quality of life, and (5) the Covid-19 pandemic has accelerated the adoption of new age technologies for disease prevention and monitoring.

Keywords: Fourth Industrial Revolution, IoT, AI, Big data, 5G, cloud computing, wearable devices, digital health, smart healthcare, personalised care, precision medicine, data management, clinical decision support, remote health monitoring, digital skills, Covid-19

1 INTRODUCTION

1.1 BACKGROUND INFORMATION

The Fourth Industrial Revolution (4IR), also known as Industry 4.0, entails the digitalisation of industries including healthcare through the use of new age technologies. The 4IR comprises mostly of Big Data analytics, Artificial Intelligence (AI), and Internet of Things (IoT) and Fifth generation (5G) wireless transmission technology (Li, 2019). The digital transformation of healthcare using data-driven Industry 4.0 technologies is called Healthcare 4.0 (Jayaraman, Forkan, Morshed, Haghighi, & Kang, 2019). Next-generation information and communications technologies (ICTs) are transforming healthcare systems through digital healthcare (e-Health). New ICTs are driving the development of more efficient, patient-centric and technology-driven healthcare systems geared towards individual healthcare services instead of the general population or one-size-fits-all approach (Li, 2019; Schiza, Neokleous, Petkov, & Schizas, 2015).

The integration of new age wireless and mobile 4IR technologies into healthcare delivery processes reduces healthcare costs in both developed and developing countries (Tortorella, Fogliatto, Espôsto, Mac Cawley, Vassolo, Tlapa, & Narayanamurthy, 2020). Disruptive 4IR technologies enable new methods for the promotion of health, prevention of diseases, diagnosis and treatment, rehabilitation, development of advanced health systems, and improved access to healthcare (Castro & Faria Araújo, 2020; Latif, Qadir, Qayyum, Usama, & Younis, 2021).

According to the World Health Organisation (WHO) 60% of lifestyle factors such as exercise and diet are directly linked to a person’s health and quality of life (Abe & Abe, 2019; Ziglio, Currie, & Barnekow, 2004). Globally, in 2018, the number of people above 65 years old exceeded those under 5 years and the gap is projected to widen by 2050 (United Nations, 2019). The combination of falling national health budgets, aging population and an elevated incidence rate of chronic illnesses and disabilities affects the delivery of affordable healthcare (Muhammed, Mehmood, Albeshri, & Katib, 2018). Chronic and lifestyle illnesses increase the costs of medical care which leads to higher morbidity and mortality rates and necessitates healthcare systems to utilise innovative ways to provide high quality healthcare services at a reduce cost (Ilan, 2021; Wolff & Jacobs, 2015).

Digital healthcare has the potential to bring about patient-centric healthcare systems which may improve patient experience and increase satisfaction from high quality healthcare services. This is through vital information on health matters, and improved decision-making on whether or not to use a health product or service. The advent of big data analytics, which can rapidly process and analyse both structured and unstructured health data, has led to the development of health information systems containing high volumes of sensor data from electronic devices and underpinned by the use of electronic medical records (EMRs) in healthcare facilities (Jung, 2019). EMRs are patient records which facilitate the automation of clinical and administrative decision-making within a healthcare service provider (Aceto, Persico, & Pescapé, 2018).

The IoT is an ecosystem made of wireless medical devices, including health wearables, which communicate through a network like the Internet without human interaction. IoT improves efficiency in healthcare delivery through better prediction, diagnostics and monitoring of patients during admission in hospital and from the comfort of their homes. There is great potential for new IoT technologies to continue to improve delivery of high quality healthcare as an enabler for smart healthcare systems (Kelly, Campbell, Gong, & Scuffham, 2020)

Artificial intelligence uses predictive analysis to identify patterns in big data to improve decision making based on clinical data from multiple structured and unstructured sources, for example, electronic health records (EHRs) and sensor data from IoT applications. Clinical Decision Support Systems (CDSS) use AI algorithms for better disease prevention, diagnostics, and remote patient monitoring. These systems also benefit the administration of smart healthcare systems and the formulation of policies for healthcare (Lysaght, Lim, Xafis, & Ngiam, 2019).

The coronavirus (Covid-19) pandemic has accelerated the adoption of 4IR technological innovations by individuals, institutions and governments (Kelly et al., 2020; Sarfraz, Sarfraz, Iftikar, & Akhund, 2021). Before the Covid-19 pandemic, there was still a marked underutilisation of digital health systems in some developing countries due to various barriers such as lack of buy-in from healthcare staff, poor ICT skills and infrastructure (Zayyad & Toycan, 2018). Regulatory barriers have also slowed the growth and proliferation of digital healthcare (Jung, 2019).

1.2 PURPOSE OF THE STUDY

The healthcare industry is undergoing digital transformation through the automation of existing processes across the value chain and new innovations for the provision of better medical products and services. The literature on the transformational role of the 4IR on healthcare is fragmented (Aceto et al., 2018) and characterised by varying conclusions on the benefits of digital health in reducing costs and improving quality of care (Tortorella et al., 2020). This systematic literature review will determine the nature and extent of the transformational role of the 4IR on healthcare by synthesising published and peer-reviewed articles on digital healthcare, identifying the main pillars of the digital transformation and current opportunities and challenges.

1.3 PROBLEM STATEMENT

The healthcare sector is faced with rising costs of healthcare services, infrastructure, and lack of skilled healthcare professionals in a highly competitive market for healthcare providers (Kanchanachitra, Lindelow, Johnston, Hanvoravongchai, Lorenzo, Huong, Wilopo, & dela Rosa, 2011; Mohamed & Al-Jaroodi, 2019). Healthcare professionals have to work through large volumes of structured and unstructured data for accurate diagnosis and treatment plans for patients. Pathological reports from remote areas are processed centrally in urban and technology-enabled hospitals by highly skilled health professionals using advanced medical equipment (Wu, Tian, & Tan, 2019). Remote areas have long distances between patients and scarce healthcare providers which limits information transfer for remote health monitoring (Pathinarupothi, Durga, & Rangan, 2019; Tamrat & Kachnowski, 2012).

4IR technologies enable healthcare providers to reduce costs and improve access to high quality healthcare by patients, in addition to operational efficiency in healthcare systems

(Al-Jaroodi, Mohamed, & Abukhousa, 2020; Free, Phillips, Watson, Galli, Felix, Edwards, Patel, & Haines, 2013). 4IR technologies also enable healthcare professionals to improve decision-making and improve patient experience (Bennett & Hauser, 2013). Given the current fragmentation of the transformational role of the 4IR on healthcare in extant literature (Aceto et al., 2018), it is important to conduct a well-structured systematic literature review of the nature and extent of the transformational role of the 4IR on healthcare.

1.4 RESEARCH QUESTION AND SUBQUESTIONS

Research questions for the SLR were developed in order to study the transformational role of 4IR applications in the healthcare industry. A research protocol was compiled for the SLR. The protocol includes the main research question, problem statement, objectives, search items, list of databases, inclusion and exclusion criteria, and quality assessment criteria. The main research question for the study outlined below:

"How is the Fourth Industrial Revolution (4IR) transforming healthcare?"

The following research sub-questions will enable me to answer the main research question:

- What are the dominant applications of 4IR technologies in healthcare?
- What is the impact of disruptive technologies on the delivery of healthcare?
- How has the Covid-19 pandemic accelerated digital transformation in healthcare?

1.5 RESEARCH OBJECTIVES

The research objectives of the study are:

- To explore the transformational role of 4IR technologies in healthcare.
- To identify dominant 4IR applications in healthcare delivery.
- To determine the impact of disruptive technologies in healthcare.
- To determine the effect of the Covid-19 pandemic on accelerating digital transformation in healthcare.

1.6 SCOPE OF THE STUDY

The research papers included in this SLR were scoped using the following inclusion and exclusion criteria. The study is limited to peer reviewed studies on how 4IR technologies are transforming the healthcare industry. Only articles published from 2016 to 2021 and contained in the three selected databases were included in the study. The start date of 2016 and end date of 2021 cover a five-year period that was selected to capture newer publications that more accurately reflect the current state of digital transformation in healthcare. The inclusion and exclusion criteria specified in sections 1.6.1 and 1.6.2, as well as the quality assessment criteria discussed in section 3.9 were used to determine the final list of research papers included in the SLR.

1.6.1 Inclusion criteria

The inclusion criteria for the study were:

- Peer-reviewed research papers published in English language or with the English translation available.
- Peer-reviewed research papers published between 2016 and 2021.
- Peer-reviewed research papers that focus on the transformational or disruptive role of the 4IR (big data, artificial intelligence and Internet of Things) on healthcare.
- Peer-reviewed research papers that focus on data-driven healthcare.
- Peer-reviewed articles on health data management systems based on 4IR technologies.

1.6.2 Exclusion criteria

The exclusion criteria for the study were:

- Duplicate research papers with multiple versions of the same paper.
- Articles that are specifically based on lessons learned or expert opinion.
- Studies that focus of on ethics and governance for digital health.
- Studies that focus on manufacturing of medicines and medical devices.

1.7 SIGNIFICANCE OF THE STUDY

This research adds to the body of knowledge on the role of 4IR technologies in transforming healthcare delivery. The study will benefit software developers and start-up companies in building 4IR applications for healthcare and to identify opportunities and challenges for new innovations in the healthcare industry. The study will identify the benefits of digital technologies for patients, healthcare professionals and healthcare providers. This should improve the trust relationship between patients, healthcare professionals and healthcare providers in a smart healthcare system.

1.8 LAYOUT OF THE MINI DISSERTATION

Chapter 1 introduces the concept of new 4IR technologies driving digital transformation in healthcare and other industries. 4IR technologies are transforming healthcare by reducing medical costs, improving quality of medical care, and efficient operations by healthcare providers. Chapter 2 provides a literature review of the new technologies, key concepts and areas in healthcare that help to explain the ongoing transformation of healthcare delivery.

Chapter 3 outlines the research design for the implementation of the SLR, taking into account the different research paradigms and research methods. Chapter 4 provides detailed discussions of my analysis of the final set of studies included in the SLR. A synthesis of the content of the articles is conducted and the contributions of each article are noted for each transformation theme in healthcare. Chapter 5 concludes the dissertation by re-visiting the research question and sub-questions, highlighting the extent to which they were answered.

2 LITERATURE REVIEW

2.1 OVERVIEW OF FOURTH INDUSTRIAL REVOLUTION AND HEALTHCARE

The healthcare industry faces challenges in delivering cost-efficient and high quality services based on universal access to healthcare and a patient-centred healthcare system (Al-Jaroodi et al., 2020). The challenges include exorbitant costs of healthcare services, shortage of healthcare professionals due to scarce skills (Hazarika, 2020; Kanchanachitra et al., 2011), and costly healthcare infrastructure (Alami, Lehoux, Denis, Motulsky, Petitgand, Savoldelli, Rouquet, Gagnon, Roy, & Fortin, 2021). There is also an increased demand for specialist healthcare services (Akay & Tamura, 2015) within a complex value chain.

The lack of collaboration between role players in the industry (Brewster, Yuan, Tan, Tangoren, & Curry, 2019) promotes competition between healthcare providers (Douglas & Ryman, 2003). The absence of collaboration in an unintegrated healthcare system triggers a scramble for technological innovations to gain a competitive edge (Al-Jaroodi et al., 2020; Roehrs, da Costa, Righi, & de Oliveira, 2017).

The healthcare industry has benefited from the adoption of 4IR technologies, through Health 4.0. Health 4.0 enables the delivery of high-quality and more cost-efficient healthcare services through a connected healthcare system (Al-Jaroodi et al., 2020; Lee, 2019). Some of the 4IR technologies adopted in Health 4.0 include Artificial Intelligence (AI), Internet of Things (IoT), Internet of Services (IoS), big data analytics, cloud computing, 5G mobile communication networks, and blockchain technology (Al-Jaroodi et al., 2020). A healthcare system must be designed to include and support “interoperability, service-orientation, modularity, real-time capabilities and other advanced functions” to be considered as Health 4.0 (Mohamed & Al-Jaroodi, 2019).

A connected healthcare system results in better patient experience and satisfaction levels through automated patient administration, remote monitoring of health status, and engagement with healthcare professionals (Al-Jaroodi et al., 2020; Lee, 2019). The new technologies also enable healthcare professionals to access patient records and diagnostic tools to tailor healthcare delivery to individual patient according to their unique health needs. Personalised healthcare provides high quality care and reduces costs (Ahamed & Farid, 2018). An efficient healthcare system is characterised by efficient resource utilisation and smart operations management. This is achieved through automation and smart algorithms for preventive maintenance of health equipment, advanced analytics to improve diagnostics, insights for disease prevention, and business process management for better process flows (Al-Jaroodi et al., 2020).

There are four groups of applications for 4IR technologies in Health 4.0 which are based on a technology-driven healthcare system (Al-Jaroodi et al., 2020). The first group focuses on provision of high-quality healthcare services to patients. The second focus area seeks to improve working conditions and automate processes for healthcare professionals. The third focuses on resource management, including human resources and physical infrastructure. The fourth focuses on the use of information technology to build and manage a healthcare system based on an advanced value chain. The 4IR technologies are not restricted to one area of application as some of them cut across an integrated healthcare system (Al-Jaroodi et al., 2020).

The provision of personalised healthcare and high-quality services can be achieved through patient management digital platforms where patients interact with healthcare providers. The healthcare providers also have the ability to communicate with patients and to conduct remote monitoring through wearable health devices. The prevention of illnesses, infectious diseases, and chronic diseases can be achieved through activities such as preventive care and health monitoring. Hospitals use electronic medical records (EMRs) and electronic health records (EHRs) for in-patient care for the processes of admission, monitoring of treatment devices, discharge of patients, and the out-patient remote monitoring during home care. (Al-Jaroodi et al., 2020).

4IR applications improve the working conditions for health professionals by assisting managers and administrators with automation of routine tasks and data-driven decision support. This includes scheduling, continuous improvement of operations, resource management, disease management, and personalised healthcare for patients. An efficient schedule also improves healthcare professionals' access to the resources required to perform their jobs such as consultation, operating rooms, and consumables. Collaboration is a key feature for 4IR applications in healthcare with a steady growth in need and usage. Collaboration involves the exchange of information between medical devices to complete medical tasks. Healthcare professionals can remotely engage among themselves or connect with experts to share case information. Administrators can collaborate for resource management and coordination of healthcare delivery during disasters and pandemics (Al-Jaroodi et al., 2020).

Healthcare systems entail thousands of resources in physical infrastructure, medical components, and human resources. Efficient resource management systems ensure that resources are available on demand and allocated through optimal scheduling that incorporates patient records, personnel schedules and usage data (Al-Jaroodi et al., 2020). 4IR applications require constant and uninterrupted connectivity to enable real-time data transfer between medical devices, and healthcare facilities (Aghdam, Rahmani, & Hosseinzadeh, 2021).

Equipment failure detection and improved maintenance can be achieved through continuous monitoring and analysis of operational data (Al-Jaroodi et al., 2020). Healthcare systems management is also a beneficiary of 4IR applications through decision support, automation, and optimisation of processes across the value chain, as well as interactions with suppliers. The usage of resources can be monitored to prevent underutilisation and wastage, and to ensure that errors are detected early and maintenance schedules are optimised (Al-Jaroodi et al., 2020; Mohamed & Al-Jaroodi, 2019).

Big data is a new technology that uses data analytics tools to transform the traditional healthcare system (Viceconti, Hunter, & Hose, 2015). Big data refers to large, complex data which may be structured, semi-structured or unstructured (Nambiar, Bhardwaj, Sethi, & Varghese, 2013). Big data analytics enable the rapid analysis and extraction of valuable information about a patient, from structured and unstructured health-related data generated by diverse sources including mobile phones, wearable sensors, patients and healthcare providers (Nambiar et al., 2013).

The use of big data analytics in healthcare improves decision-making by healthcare professionals and to provide timely and personalised healthcare to patients (El Aboudi & Benhlima, 2018). Big data analytics comes with a risk of lack of security and privacy for patients' data as it is open to misuse and cyber theft. Hence strict measures should be put in place to safeguard the data from unauthorised access (Ambigavathi & Sridharan, 2018).

AI is positioned to complement health professionals and not as their substitute towards the reduction of morbidity and mortality rates among patients (Xu, Xue, & Zhang, 2019). AI technologies, including neural networks, machine learning, deep learning, and robotics have been widely adopted by healthcare professionals. This enables the provision of high quality healthcare to patients and optimisation of resource management in healthcare institutions (Yoon & Lee, 2019). AI provides smart algorithms which enable healthcare professionals to use clinical data, including both EMR and EHR data, for precision medicine and to tailor optimal treatment to individual patient (Bohr & Memarzadeh, 2020). AI technologies reduce healthcare costs by transforming healthcare models from reactive disease treatment to proactive health management through continuous health monitoring, disease prevention and early diagnosis (Bohr & Memarzadeh, 2020; Lee & Yoon, 2021).

One of the challenges for AI in healthcare is lack of trust in the technology by healthcare professionals and patients. This trust deficit is primarily based on psychological factors and not necessarily the efficiency of the AI applications (Yokoi, Eguchi, Fujita, & Nakayachi, 2020). It is easier to develop a psychological trust relationship between a doctor and a patient which produces a placebo effect and improves the effectiveness of the treatment (Kaptchuk & Miller, 2015). Patients with relatively limited experience with AI applications find it difficult to develop a trust relationship with the AI system without the assurance of the healthcare professional about their effectiveness (Castro & Faria Araújo, 2020; Lee & Yoon, 2021). The growth of AI is inevitable in society as its benefits far outweigh its limitations (Yokoi et al., 2020).

The use of IoT technologies has grown rapidly across many industries including healthcare (Qadri, Nauman, Zikria, Vasilakos, & Kim, 2020). IoT is an Internet connected network of smart devices enabling remote communication between machines (machine-to-machine) and communication between people and machines (Lin, Yu, Zhang, Yang, Zhang, & Zhao, 2017). The Internet and IoT technology form the basis for an e-Health system which reduces healthcare costs and improves the quality of healthcare services (Shaikh, Parvati, & Biradar, 2018). Body Sensor Networks (BSNs) are the IoT technologies that support healthcare through the use of sensors placed on the human body (Yang, Wang, Gravina, & Fortino, 2017). BSNs include smart wearable devices which conduct health monitoring of individuals for early diagnosis of health problems and identification of personalised treatment plans (Qiu, Wang, & Xie, 2017).

5G wireless technology is an Internet-based mobile network model in telecommunications that provides increased device connectivity, cheaper and low latency data transfer at higher capacity and speed (Jain, Acharya, Jakhar, & Mishra, 2018). 5G is a combination of 4IR technologies including big data, IoT, cloud computing, and AI (Li, 2019). The introduction of the new technologies in healthcare requires enhanced security and privacy of proprietary and personal data (Lin et al., 2017; Qadri et al., 2020). IoT technologies, for example, have security features that ensure data confidentiality and that only authorised person use the data without tempering with them (Chopra, Gupta, & Lambora, 2019; Lin et al., 2017).

2.2 APPLICATIONS OF FOURTH INDUSTRIAL REVOLUTION TECHNOLOGIES IN HEALTHCARE

2.2.1 Precision medicine: Personalised healthcare services

Precision medicine is a predictive, preventive, personalised, participatory healthcare delivery model (Wiweko & Zakirah, 2020) that tailors treatment plans to individuals or groups with similar disease profile, diagnosis, prognosis or response to treatment (Bohr & Memarzadeh, 2020). Smart algorithms analyse large data sets for accurate diagnosis and identification of optimal treatment plans based on individual characteristics for a patient. Wearable sensors and other health applications collect health data from individuals using machine-learning algorithms to identify patterns in the data in order to determine more personalised treatment strategies (Bohr & Memarzadeh, 2020).

IoT technologies contribute to personalised healthcare in terms of assistive care, remote diagnostics and monitoring of health in remote areas which may lack qualified healthcare professionals and other healthcare resources, for example, health equipment (Ahamed & Farid, 2018). Distributed computing enables rapid data sharing from connected IoT devices to take preventive, predictive and diagnostic decisions that improve quality of service for patients through personalised care (Uslu, Okay, & Dursun, 2020). Big data analytics enables the rapid extraction of data from large data sets for healthcare providers to select the right decisions for individual patients at the right time (El Aboudi & Benhlima, 2018).

Genomics, the study of genetic material in living organisms, contributes to the development of personalised medicine through patient-specific data on biological markers (biomarkers), for example, deoxyribonucleic acid (DNA) profile. Individual patient characteristics have a bearing on the efficacy of medicines through more personalised medicines (Bhardwaj, Sethi, & Nambiar, 2014). Machine learning, a major branch of AI, uses smart algorithms to enhance genomics-based precision medicine through its combination with physiological and functional genomics (Williams, Liu, Regner, Jotterand, Liu, & Liang, 2018). The –omics data, that is, genomics, proteomics, metabolomics and other data types are inherently big data and the foundation for precision medicine (Cosgriff, Celi, & Stone, 2019).

2.2.2 Telemedicine and remote health monitoring

Telemedicine supports the provision of healthcare services using technological innovations to enable access to remote areas through communication between a specialist, local healthcare professional and a patient (Avila, Sanmartin, Jabba, & Jimeno, 2017). The technologies enabling telemedicine include live videos, images shared through video calls or emails for sending and receiving patients' information (Shaikh, Memon, Memon, & Misbahuddin, 2009). Smart health systems use IoT technology to enable seamless remote health monitoring of a patient's vital data and other clinical data by healthcare professional, for example glucose (blood sugar) level, heartbeat and blood pressure (Shaikh et al., 2018). Remote health monitoring using wearable devices and telemedicine enables healthcare professional to remotely monitor and manage chronic ailments such as diabetes, heart disease, and asthma (Low, 2007).

Real-time video calls in telemedicine enable remote patient examination to determine appropriate treatment. However, this is expensive and less practical in developing countries due to high telecommunication costs. Alternatively, the store-and-forward telemedicine method stores the patient's clinical data which is forwarded to healthcare specialists by local healthcare professionals aided by IoT technologies (Hameed, Bajwa, Sarwar, Anwar, Mushtaq, & Rashid, 2021). 5G technology mitigates the time and distance limitations faced by healthcare institutions in implementing telemedicine through monitoring of smart devices. The increased bandwidth from 5G technology also makes it possible to transmit real-time video data which promotes the use of the video method in telemedicine (Hameed et al., 2021).

2.2.3 Decision support and healthcare resource management

Clinical Decision Support Systems (CDSS) use big data and AI to provide real-time decisions to healthcare professionals and patients on the best choice of medical care (Lysaght et al., 2019; Naqa, Kosorok, Jin, Mierzwa, & Ten Haken, 2018). CDSSs help healthcare administrators to optimise resource allocation and reduce healthcare costs (Lysaght et al., 2019). The effectiveness of CDSSs to improve quality of medical care and reduce medical costs has not been universally accepted in the healthcare industry (Naqa et al., 2018). Increasing amounts of healthcare data and advancements in cloud computing and mobile technologies have improved the perception of CDSSs on their effectiveness to improve medical care and reduce medical costs (Naqa et al., 2018).

4IR technologies can resolve the uneven distribution of medical resources, improve efficiency through an integrated healthcare delivery system that promotes fairness and access to healthcare services (Xu et al., 2019). Scarce medical resources are mostly available in big cities and other urban areas which may lead to crowding as patients from rural areas search for medical services in the big cities. Crowding in hospitals can be better managed through an optimal allocation of medical resources to ensure that patients receive high-quality care (Wu et al., 2019). Smart hospitals, enabled by 4IR technologies, use networked healthcare to optimise resource allocation through faster decision making (Uslu et al., 2020).

2.3 CURRENT OPPORTUNITIES AND CHALLENGES OF FOURTH INDUSTRIAL REVOLUTION IN HEALTHCARE

2.3.1 Opportunities of fourth industrial revolution in healthcare

The steady growth of 5G mobile networks has the potential to increase the use of AI in healthcare. 5G technology transmits large multimedia files, for example medical images, and low latency real-time video will enhance the adoption rate for video calls in telemedicine (Lee & Yoon, 2021). Healthcare 5.0 is an integrated platform that combines AI algorithms, 5G and IoT and could usher in a smart healthcare system with increased automation (Aghdam et al., 2021; Mohanta, Das, & Patnaik, 2019). Healthcare 5.0 enables remote patient monitoring, automated diagnosis and treatment of diseases (Aghdam et al., 2021; Mohanta et al., 2019).

Mobile health (mHealth) is one of the growth areas from the induction of 5G and IoT technologies in a smart healthcare system. mHealth is a combination of mobile networks, wearable sensors, smartphones, and smart medical technologies to enable telemedicine (Lloret, Parra, Taha, & Tomás, 2017). Big data, IoT and AI technology are driving research on the integration of conventional EHRs with wearable sensor data for smarter personalised healthcare services (Vuppalapati, Ilapakurti, & Kedari, 2016). By the year 2021, the number of connected smart devices is projected to be three times the number of people in the world. An increased number of devices will have medical applications and integrated sensors fitted and this provides disruptive opportunities in healthcare (Alexander, McGill, Tarasova, Ferreira, & Zurkiya, 2019).

Digital applications provide a number of opportunities in healthcare through improved care treatment, diagnostics, disease prevention through increased interaction between patients and healthcare professionals. Smart algorithms enable healthcare professionals to reduce levels of medical errors and enhance the quality of healthcare services through more efficient diagnostics processes. Autonomous AI applications streamline a healthcare system's operations resulting in reduced costs for diagnosis and treatment (Hazarika, 2020).

Start-up companies, with increased investor interest, are increasingly developing new technologies for medical imaging using predominantly AI, Blockchain, visualisation technologies, and Virtual Reality (VR) for improved diagnosis and treatment (Alexander et al., 2019; Lin, Mahoney, & Sinsky, 2019). A wide proliferation of AI applications in healthcare for the achievement of technology-enabled personalised care can lead to high quality care and reduced healthcare costs (Lee & Yoon, 2021).

AI applications will not necessarily replace healthcare professionals but should augment them to allow them to engage in more meaningful interactions with their patients and improve patient experience (Goldsack & Zanetti, 2020; Xu et al., 2019). Automated AI applications can replace manual tasks while creating new job opportunities.

2.3.2 Challenges of fourth industrial revolution in healthcare

There is still marked underutilisation of digital health systems in both developed and developing countries due to various barriers such as lack of buy-in from healthcare professionals, poor ICT skills and inadequate infrastructure (Meskó, Drobni, Bényei, Gergely, & Győrffy, 2017; Zayyad & Toycan, 2018). Even though some applications have been implemented in healthcare, digital technologies show theoretical potential but face challenges in translating a proof of concept to successful implementation at scale (Alami et al., 2021; Latif et al., 2021; McNabb, Myers, Wicking, Lei, & Xiang, 2018; Qadri et al., 2020).

The Internet is the foundation for IoT technologies but it raises a number of challenges related to the uninterrupted connection, and protection of proprietary and personal data from all forms of unauthorised access or data loss (Aghdam et al., 2021; Chopra et al., 2019; Onik, Chul-Soo, & Yang, 2019). The "digital divide" also promotes the unequal access to digital health technologies and quality medical care between affluent and poor communities (Erikainen, Pickersgill, Cunningham-Burley, & Chan, 2019). Healthcare providers have not fully adopted the innovations from cloud computing and IoT due to data security fears in a distributed data sharing environment (Celesti, Ruggeri, Fazio, Galletta, Villari, & Romano, 2020).

The lack of interoperability and standardisation in data acquisition and management, has led to underutilisation of wearables, voice-enabled healthcare, and speech recognition technologies in healthcare (Ahad, Tahir, Aman Sheikh, Ahmed, Mughees, & Numani, 2020; Latif et al., 2021; Orphanidou, 2019; Sartori, 2020). Voice-enabled smart technologies face challenges of limited data and variations in languages spoken worldwide to successfully build a speech-based healthcare system (Latif et al., 2021). AI applications and big data face limitations in terms of poor-quality healthcare data that lacks interoperability to facilitate both machine learning and deep learning (Tobore, Li, Yuhang, Al-Handarish, Kandwal, Nie, & Wang, 2019; Wiens & Shenoy, 2018).

Proprietary communication protocols by different sensor manufacturers prevents sensors from communicating with each other and this restricts the required interconnectedness for IoT devices (Aghdam et al., 2021; Dimitrov, 2016; Meinert, Van Velthoven, Brindley, Alturkistani, Foley, Rees, Wells, & de Pennington, 2018). Data quality is also affected by poor business process management and data management systems. Biomedical informatics, including health informatics, can resolve the lack of standardisation and poor data management systems through the construction of big-data enabled learning health systems (Scott, Dunscombe, Evans, Mukherjee, & Wyatt, 2018).

Poor quality data is a significant challenge for the application of big data systems in healthcare which leads to inaccurate analysis and decisions (Orphanidou, 2019). The poor data quality, inadequate volume of training data, and poor model performance have slowed the adoption of deep learning applications in healthcare, for example, clinical decision support (Hirose, Wakata, Tagi, & Tamaki, 2020; Miotto, Wang, Wang, Jiang, & Dudley, 2018). EMRs have great potential to facilitate digital health but suffer data entry errors that lead to adverse diagnostic and treatment outcomes (Lun, 2018).

Regulatory barriers have also slowed the growth and proliferation of digital technologies in healthcare (Jung, 2019; Kelly et al., 2020; Mattei, 2020). Increasingly strict regulatory requirements for data privacy and security make sharing of healthcare data difficult between public and private users (Qadri et al., 2020; Zheng, Sun, Mukkamala, Vatrapu, & Ordieres-Meré, 2019). In the absence of an appropriate legal framework, it is difficult to allocate accountability between healthcare professionals, healthcare facilities and AI applications when a medical error or accident occurs (Hazarika, 2020; Lee & Yoon, 2021). The source of the error may be technical which may point to defective design and programming of the smart algorithms (Lee & Yoon, 2021; Xu et al., 2019).

Organisational readiness, managerial and operational challenges may also be responsible for the failure to adopt and use AI applications in the healthcare sector (Alami et al., 2021; Lee & Yoon, 2021; McNabb et al., 2018). In response to the growth of AI applications in healthcare, healthcare providers have been forced to outsource ICT skills and human resource management. Modern hospitals have evolved in line with the less bureaucratic but more integrated and networked healthcare model. The new governance system for networked healthcare has led to a perceived lack of control by hospital administrators (Lee & Yoon, 2021).

Ethical and legal issues around AI and other 4IR applications have become paramount to prevent their misuse through uncontrolled human power and to ensure consistency with societal standards, norms and laws (Cohen, Gostin, & Weitzner, 2020; Gerke, Minssen, & Cohen, 2020; Lee & Yoon, 2021). The rapid growth of 4IR applications in a fast-changing healthcare industry requires a comprehensive ethics and governance framework for regulated use of smart algorithms and to ensure accountability and confidentiality of patient data (Erikainen et al., 2019; Latif et al., 2021; Lee & Yoon, 2021). The commercialisation of patient data generated from multiple platforms including social media can be sold to third parties for profit and this raises ethical and privacy issues (Erikainen et al., 2019). Ethical considerations are hindering the pace of adoption for AI and other 4IR technologies (Latif et al., 2021; Mattei, 2020).

4IR applications must improve patient care since it is the primary goal for healthcare and should be prioritised ahead of socio-economic factors such as income and labour relations in order to be widely adopted in healthcare (Fogel & Kvedar, 2018). Humans play a significant and complementary role in the successful implementation of digital technologies in healthcare whereby automated systems include human factors in their design, for example, perception and induction. In environments where life is at risk, it is crucial to understand the trust relationship between human beings and digital applications (Asan, Bayrak, & Choudhury, 2020; Castro & Faria Araújo, 2020).

The acceptance of digital technologies by health professionals is based on organised change management in their organisations to ensure their accuracy, integration with existing systems and ease of use (Kelly et al., 2020). Digital applications have their comparative scientific validity being continuously questioned against conventional healthcare activities. For example, clinical decisions based on big data insights compared with outcomes from clinical trials (Chen, Guzauskas, Gu, Wang, Furnback, Xie, Dong, & Garrison, 2016). Healthcare professionals, once they are convinced about the safety and security of digital applications, can bridge the trust gap between digital applications and patients by assuring patients (Kelly et al., 2020; Lee & Yoon, 2021).

The economic benefits for the automation of routine healthcare tasks and diagnosis from clinical data are difficult to determine since it is very costly to set up the infrastructure and equipment (Vandenberg, Durand, Hallin, Diefenbach, Gant, Murray, Kozlakidis, & van Belkum, 2020). It is costly to monitor the performance of IoT devices in a smart healthcare system and the high cost of healthcare devices is prohibitive for poor people (Aghdam et al., 2021).

Unless the digital technologies are fully autonomous, they require additional human resources for extended supervision. Automated laboratory tests, for example, require a round-the-clock testing and supervision model, which may drive up the costs per test unless it is offset by higher volumes of tests (Vandenberg et al., 2020).

2.4 CONCLUSION

4IR technologies are continuously transforming healthcare for patients, healthcare professionals, and healthcare providers. Conventional healthcare has been transformed to digital, intelligent, distributed, and participatory smart healthcare. Digital health use cases include real-time diagnostics and treatment outcomes through remote health monitoring. The use cases reflect transformation of key areas of healthcare include personalised care, precision medicine, telemedicine, mobile health, and clinical decision support. Clinical decision support uses integrated 4IR technologies to improve the quality of medical care and reduce costs of medical services. There are many opportunities for more innovations in technology to be developed and adopted in healthcare. Various legal, social, and technological challenges limit the pace of adoption of new technologies in healthcare.

3 RESEARCH METHOD

3.1 INTRODUCTION

This chapter describes the research paradigms and research strategies that were considered in designing the study. Section 3.2 provides an overview of the philosophical assumptions that underlie the three research paradigms that are typically followed in information systems (IS) as part of the motivation for the selection of one paradigm that is most applicable for the study. Section 3.3 describes the different types of research strategies. Section 3.4 outlines the design of the research in line with the chosen paradigm and research strategy. Section 3.5 to 3.9 discussed the process that was followed to identify the research papers that were included in the systematic literature review (SLR), including the Prisma Flow Chart and quality assessment process. A brief description of the data analysis approach is given in section 3.10 while the ethical considerations are in section 3.11. The conclusion to the chapter is in section 3.12.

3.2 OVERVIEW OF RESEARCH PARADIGMS IN INFORMATION SYSTEMS RESEARCH

There are five philosophical paradigms which influence the choice of research method for undertaking a study. The paradigms outline a set of assumptions or ways to understand particular aspects of the world. The research paradigms are positivism, interpretivism, critical research, postmodernism, and pragmatism (Saunders, Lewis, Thornhill, & Bristow, 2019). Positivism, interpretivism and critical research are the three paradigms used in Information Systems (IS) research. The five research paradigms are outlined below.

3.2.1 Positivism

Positivism is generally linked with quantitative studies and experiments that emphasise objectivity based on measurement as opposed to subjective perceptions (Saunders et al., 2019). This paradigm relies heavily on empirical studies and rationalism and is not influenced by the researcher’s views but seeks to find universal laws and generalisability. Positivism emphasises hypothesis testing and uses quantitative and statistical analysis to determine cause and effect, correlations, and identify underlying regularities (Ryan, 2018; Saunders et al., 2019).

3.2.2 Interpretivism

Interpretivism is effectively the opposite of positivism and uses a smaller amount of empirical and qualitative data as it searches for dynamic, socially constructed meaning using qualitative analysis of data for people in social settings (Saunders et al., 2019). This paradigm has various subjective realities and multiple interpretations and contextual perspectives observed by a researcher that is not entirely independent of the study through their beliefs and values (Ryan, 2018; Saunders et al., 2019). The interpretivism paradigm will be adopted for the SLR in this study since the outcome of the analysis of primary studies that are included in the SLR will be influenced by the interpretations of the researcher.

3.2.3 Critical research

The Critical Research paradigm seeks to find contradictions and conflicts in existing world views and identify their underlying power structures using a mix of subjective and objective instruments (Saunders et al., 2019). This paradigm uses smaller amounts of empirical data and acknowledges that the researcher is not entirely independent of the study. A comprehensive and in-depth analysis for critical explanation and to identify a transformative future is conducted (Ryan, 2018).

3.2.4 Postmodernism

Postmodernism, sometimes confused with postmodernity that identifies a specific historical era, seeks to explore the role of language and power dynamics in shaping dominant views and suppressing alternative ways of seeing and thinking (Saunders et al., 2019). Postmodernists promote marginalised views by deconstructing dominant views to identify gaps that indicate the absence of suppressed views (Saunders et al., 2019). Power dynamics between the researcher and respondents determine the outcomes of the research and this requires transparency on morals and ethics (Saunders et al., 2019).

3.2.5 Pragmatism

Pragmatism seeks to identify the relevance of theories, concepts, ideas, hypotheses, and research findings in enabling thought and successful action (Saunders et al., 2019). The researcher identifies practical solutions to problems in order to inform future practice (Saunders et al., 2019). Pragmatism reconciles objectivism and subjectivism which characterise positivism and interpretivism, respectively (Saunders et al., 2019; Yvonne Feilzer, 2010). Pragmatists apply different methods and use different types of knowledge to address a research problem and research question by providing practical solutions (Saunders et al., 2019; Yvonne Feilzer, 2010).

3.3 RESEARCH STRATEGIES

There are a number of strategies that could be employed to carry out a research. These include experiments, surveys, case studies, action research, grounded research, and ethnography (Saunders, Lewis, & Thornhill, 2007). A laboratory or field experiment may be the setting for a researcher that measures the results of a treatment intervention in a study group (Williams, 2007). A case study is an in-depth research study of a program, event or object, within a given time period and place, and uses multiple data sources to draw lessons learned and identify patterns linked to theories (Creswell & Creswell, 2017; Williams, 2007).

Ethnography differs from case studies as they focus on a group with common culture in a natural setting and over an extended period, focusing on changes to the culture over time (Williams, 2007). Grounded theory allows the data collected to inform the theory, instead of extracting theories from existing literature, in the study of people’s actions and interactions (Creswell & Creswell, 2017; Williams, 2007). A survey is used to collect data from a sample of observational units. A questionnaire with a set of standardised questions is the predominant method used in surveys. The results of surveys from a representative sample can be used to make inferences or generalisation to the entire population (Williams, 2007).

Researchers use SLRs to make sense of existing literature to determine the current state and quality of information regarding a research question (Siddaway, Wood, & Hedges, 2019). A research question, search methodology, and inclusion and exclusion criteria must be formulated for a SLR. Also, a filter for relevant studies, structured critique or appraisal of each study, and, finally, a synthesis of the findings from the different eligible studies into outcomes linked to the research question must be conducted (Siddaway et al., 2019). SLRs identify gaps and areas of improvement in current literature and determine whether theoretical hypotheses are supported or contradicted by empirical evidence (Siddaway et al., 2019).

3.4 RESEARCH DESIGN

A research design provides a plan or framework that outlines how a study will go about answering the research question in line with a stated research strategy or method. The research design ensures that data collection is geared towards answering the research question (Durrheim, 2006).

This study utilised the SLR research method in line with the interpretivism philosophical paradigm and mixed-methods approach incorporating both quantitative and qualitative analysis. SLRs also take into consideration whether the studies included in the review are both qualitative and quantitative. Research findings that inform policy and are user-friendly require an integrated or mixed methods approach to account for all studies (Brannen, 2005; Mertens, 2018).

3.5 DATA SOURCES AND SEARCH STRATEGY

3.5.1 Source selection

Electronic databases were used to search for the studies that were included in the SLR. The JMIR journal was of particular interest but was not treated as a separate database but a fully-indexed subset of MEDLINE and PubMed Central. PubMed Central was selected over the regular PubMed because of its coverage of full text articles. The EBSCO Discovery Service (EDS) was used to access fully-indexed MEDLINE articles as it streamlines access to various partner databases and improves availability of full-text files.

The following electronic databases were searched without conducting an extended search for additional records from other sources.

- PubMed Central
- Institute of Electrical and Electronics Engineers (IEEE)
- MEDLINE

3.5.2 Search terms

The search terms were developed to cater for the variations in the names used for 4IR, healthcare and transformation. The terms were then combined using the Boolean "AND" operator to ensure that the search results included sources that would enable me to achieve the research objectives.

The combined search terms were:

("Fourth Industrial Revolution" OR "4IR" OR "Industry 4.0" OR "Internet of Things" OR "IoT" OR "Big Data" OR "Artificial Intelligence" OR "AI" AND "Health" OR "Healthcare" OR "Health care" OR "Health 4.0" OR "Health Delivery" OR "Digital Health" OR "EHealth" OR "E-health" AND "Transformation" OR "Transform*" OR "Disruptive Technologies" OR "Disrupt*")

3.6 SELECTION CRITERIA

Study selection

The inclusion and exclusion criteria that were used to select sources that were included in the SLR are listed in sections 1.6.1 and 1.6.2 respectively. Only peer-reviewed journal articles which were published between 2016 and 2021, written in or translated to English, and focused on the transformational role of 4IR were prime targets for inclusion. The SLR included quantitative and qualitative studies which were based on empirical studies. Non-empirical studies and those that focused on governance and policy issues were excluded from the SLR.

3.7 PRISMA FLOWCHART

The Prisma Flow Chart, illustrated in Figure 3.1, shows the steps taken to identify the articles that were included in the study. The selection of electronic databases was based on the listing and indexing of medical journals, for example, the Journal of Medical Internet Research (JMIR) and MEDLINE. A background study of the databases showed that the databases had overlaps in terms of the targeted journals which resulted in the choice of three databases shown in section 3.5.1. The initial search based on the search terms yielded 12 804 sources. Duplicates were removed after the initial application of the inclusion/exclusion criteria and 5 473 sources remained for screening.

The sources were first screened by title which yielded 1439 articles. The remaining articles were screened by abstract produced which produced 204 articles. The 204 articles were then screened for eligibility. The selection process then excluded 120 articles through a full text quality assessment which yielded 84 articles that were included in the literature review.

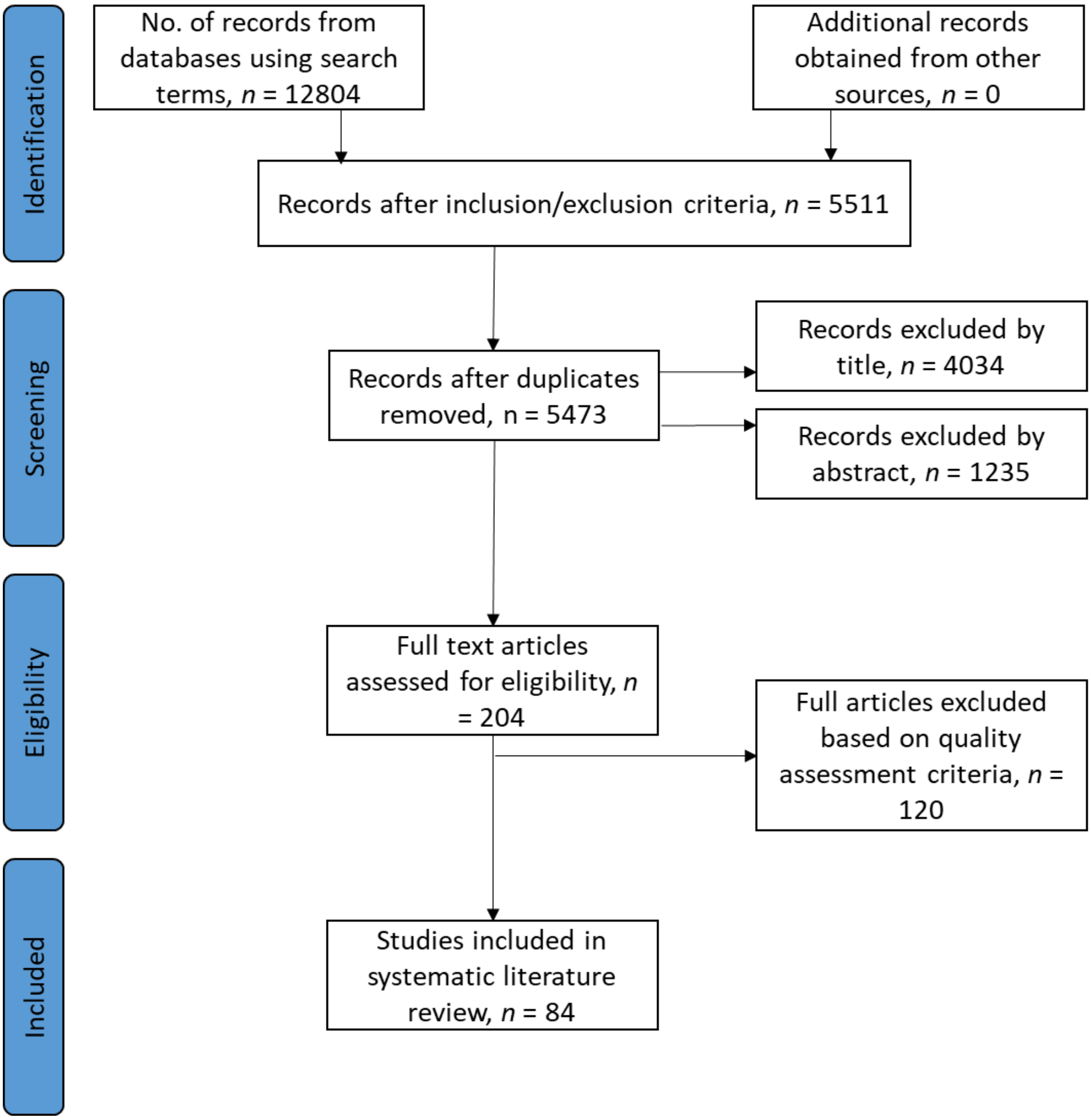

Figure 3.1: Research papers selection process

Adapted from: (Moher, Liberati, Tetzlaff, Altman, & Group, 2009)

3.8 CITATION MANAGEMENT AND EXTRACTION

The citations were imported directly into EndNote, together with their abstracts. The articles were sorted by Author and exported into Microsoft Excel for screening and management. A Microsoft Excel template was used to manage the source database, screening outcome, and eligibility status using the quality assessment criteria for each article. The quality assessment criteria, discussed in section 3.9, were applied on the introduction, methodology and findings sections of each article.

3.9 QUALITY ASSESSMENT

The quality assessment criteria were applied to the 204 articles which remained after the screening by abstract in order to determine their eligibility for final inclusion in the study. The quality assessment criteria were:

- QA1: Is the article based on an empirical study?
- QA2: Does the article clearly define the 4IR field under consideration, i.e. big data, artificial intelligence, or Internet of things?
- QA3: Does the article clearly discuss the application of 4IR in an identifiable major healthcare service or clinical decision support, i.e. health promotion, disease prevention, diagnosis and treatment, rehabilitation, clinical services and resource management?
- QA4: Is the article explicit in illustrating the transformational or disruptive role of 4IR, i.e. big data, artificial intelligence, or Internet of things, in healthcare?

A score was allocated for each criterion where a value of 1 (one) was given for meeting the criteria and 0 (zero) otherwise. Figure 3.2 shows that four articles had a score of 1 (one), 16 articles had a score of 2 (two), 70 articles had a score of 3, and 100 articles had a maximum score of 4 (four). Only articles that met all the quality assessment criteria were retained for the SLR analysis. The inclusion and exclusion criteria were further applied on the 100 articles with a score of 4 (four). Further, articles without keywords which were excluded from the final list. A total of 84 articles were retained for the SLR analysis after the application of the extended quality assessment criteria. A detailed list of the quality assessment scores is shown in Appendix D.

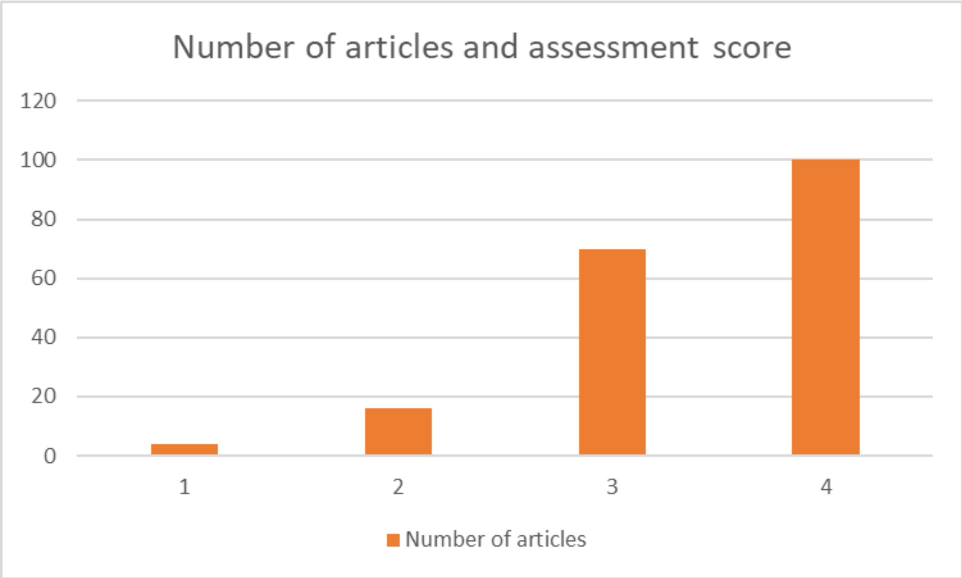

Figure 3.2: Number of articles and quality assessment score

3.10 DATA ANALYSIS

The content analysis study approach uses a thorough and systematic review of a group of research articles, audio and visual media, books, and newspapers to identify behavioural patterns, themes and biases (Leedy & Ormrod, 2005; Williams, 2007).

A thematic analysis of the research articles in the SLR was used to determine the current status of the transformation of healthcare by digital technologies. Quantitative and qualitative analysis results were compiled using graphs and tables with a discussion of each identified theme. The analysis results were then linked to the main research question and research sub-questions.

3.11 ETHICAL CONSIDERATIONS

Research ethics requires the researcher to obtain consent from all respondents in a research study where a researcher interacts with the respondents. Respondents should not be seen to be merely fulfilling a passive role of providing data or getting tested but should be treated equally, and afforded a sense of dignity and self-worth (Oliver, 2010). The role of a researcher should be distinct from their professional role to ensure that there is no conflict of interest resulting in an ethical dilemma (Oliver, 2010).

This research complied with the University of Pretoria's Policy and Procedures for Responsible Research (University of Pretoria, 2007) and the Code of Ethics for Scholarly Activities (University of Pretoria, 2021). At the time of conducting this research, the Faculty of Engineering, Built Environment and Information Technology (EBIT) research ethics committee did not require ethical clearance for studies that employ the SLR method.

3.12 CONCLUSION

The SLR was identified as a suitable research method for the interpretivism philosophical paradigm used in the study. A thematic analysis approach was used to analyse the content of the research articles included in the SLR to identify themes on the transformation of healthcare by 4IR technologies. Three databases were used to identify articles, namely, PubMed Central, Institute of Electrical and Electronics Engineers (IEEE), and MEDLINE. The search used search terms, inclusion and exclusion criteria, and quality assessment to identify the final set of 84 articles reflected in the Prisma Flow Chart.

4 ANALYSIS OF RESEARCH PAPERS AND DISCUSSION

4.1 QUANTITATIVE ANALYSIS OF RESEARCH PAPERS INCLUDED IN THE SYSTEMATIC LITERATURE REVIEW

This section provides results of the quantitative analysis of the research papers included in the SLR according to the database where they were retrieved, the year of publication and research method used.

As illustrated in Table 4.1, the largest number of research papers (47) were retrieved from PubMed Central. This is followed by MEDLINE (EBSCO) with 28 articles. Only nine papers were retrieved from the IEEE database.

Table 4.1: Number of articles by source database

Database	Number of articles	Percentage
PubMed Central	47	56%
IEEE	9	11%
MEDLINE (EBSCO)	28	33%
Total	**84**	**100%**

Table 4.2 illustrates the type of research method (that is, quantitative, qualitative and mixed-method) that were employed by the research papers included in the SLR. Nineteen research papers employed the quantitative research method, 58 used a qualitative method while the remaining seven followed the mixed method research.

Table 4.2: Number of articles by research method

Research method	Number of articles	Percentage
Quantitative	19	23%
Qualitative	58	69%
Mixed-method	7	8%

Table 4.3 shows the number of articles by research type for each database. The qualitative method dominates in all three databases at 35, five, and 16 articles for PubMed Central, IEEE and MEDLINE (EBSCO) respectively. The mixed-method has the lowest

number of articles for IEEE and MEDLINE with one article each, respectively. PubMed Central has the same number of quantitative and mixed-method articles at 5 (five).

Table 4.3: Number of articles by research method per database

Database	Research method	Number of articles	Percentage per database
PubMed Central	Quantitative	5	11%
	Qualitative	37	79%
	Mixed-method	5	11%
IEEE	Quantitative	3	33%
	Qualitative	5	56%
	Mixed-method	1	11%
MEDLINE (EBSCO)	Quantitative	11	39%
	Qualitative	16	57%
	Mixed-method	1	4%

The number of publications per year is illustrated in Figure 4.1. As shown in Figure 4.1, 32 of the research papers included in the SLR were published in 2020. This is followed closely by 19 papers published in 2019. Thirteen articles were published in 2018, with 11 in 2021. The number research papers published in 2017 and 2016 were 5 (five) and 4 (four) respectively.

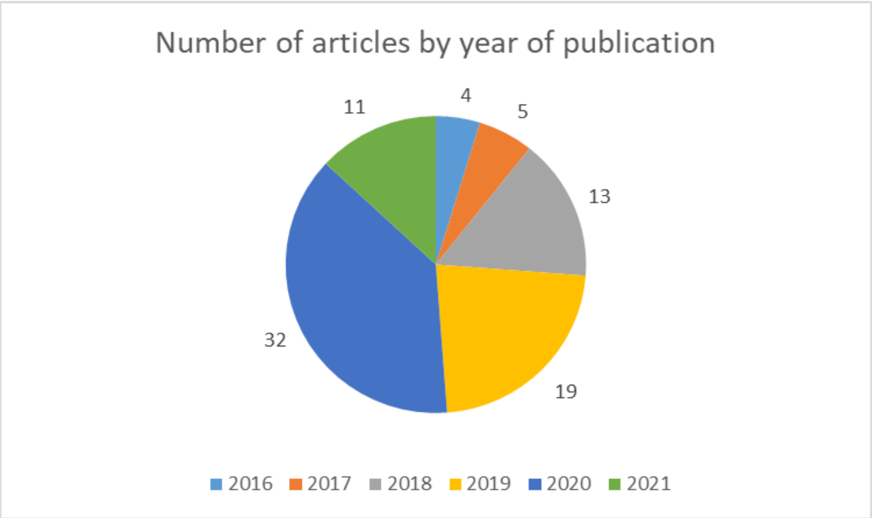

Figure 4.1: Number of articles by year of publication

4IR technologies in healthcare complement each other and this presents many overlaps. Figure 4.2 shows the number of articles for individual and combinations of 4IR technologies in line with each article's focus area.

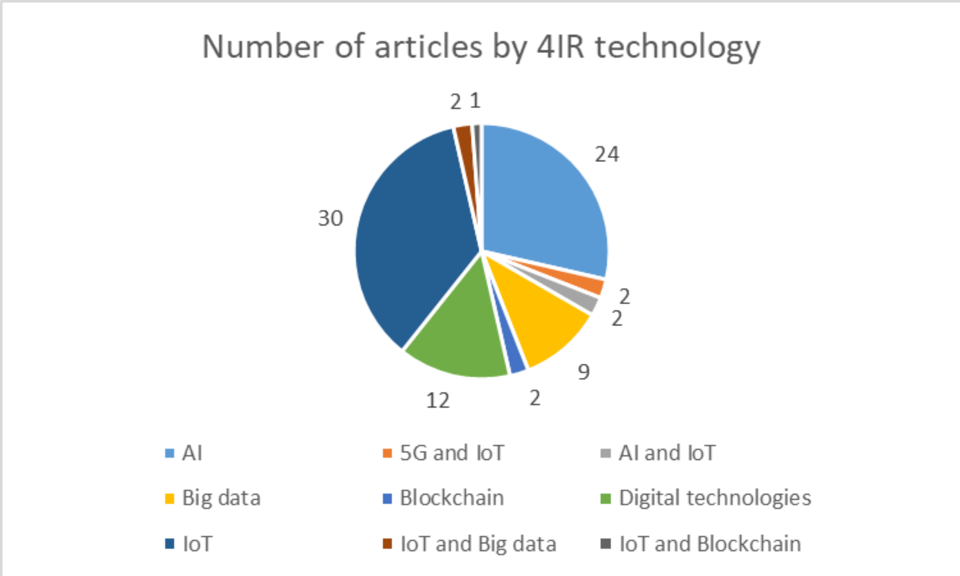

Figure 4.2: Number of articles for by 4IR technology

The highest number of articles (30) focused on the application of IoT in healthcare. The second highest number of articles (24) studied AI applications in healthcare. Digital technologies, a generalised composite of different technologies was studied in 12 of articles while Big data was covered in 9 of articles. The composite of IoT and Blockchain had the smallest number at 1 (one).

4.2 TRANSFORMATIONAL ROLE OF THE FOURTH INDUSTRIAL REVOLUTION ON HEALTHCARE

The transformational role of the 4IR on healthcare was evaluated using the concept of digital transformation. Digital transformation can be defined as the use of digitalisation and digital innovation to drive change in business practices, organisational structure and business processes to achieve organisational or industry transformation (Osmundsen, Iden, & Bygstad, 2018). Digital health, including electronic health (eHealth) and networked healthcare, use continuous innovations in technology and computing to transform healthcare (Kukafka, 2019).

The themes for transformation of healthcare in relation to the research question and sub-questions are listed below:

- 4IR technologies driving transformation in healthcare
- Digital transformation areas in healthcare
- Impact of digital transformation in healthcare

Figure 4.3 illustrates the themes and sub-themes that emerged from the research papers included in the SLR.

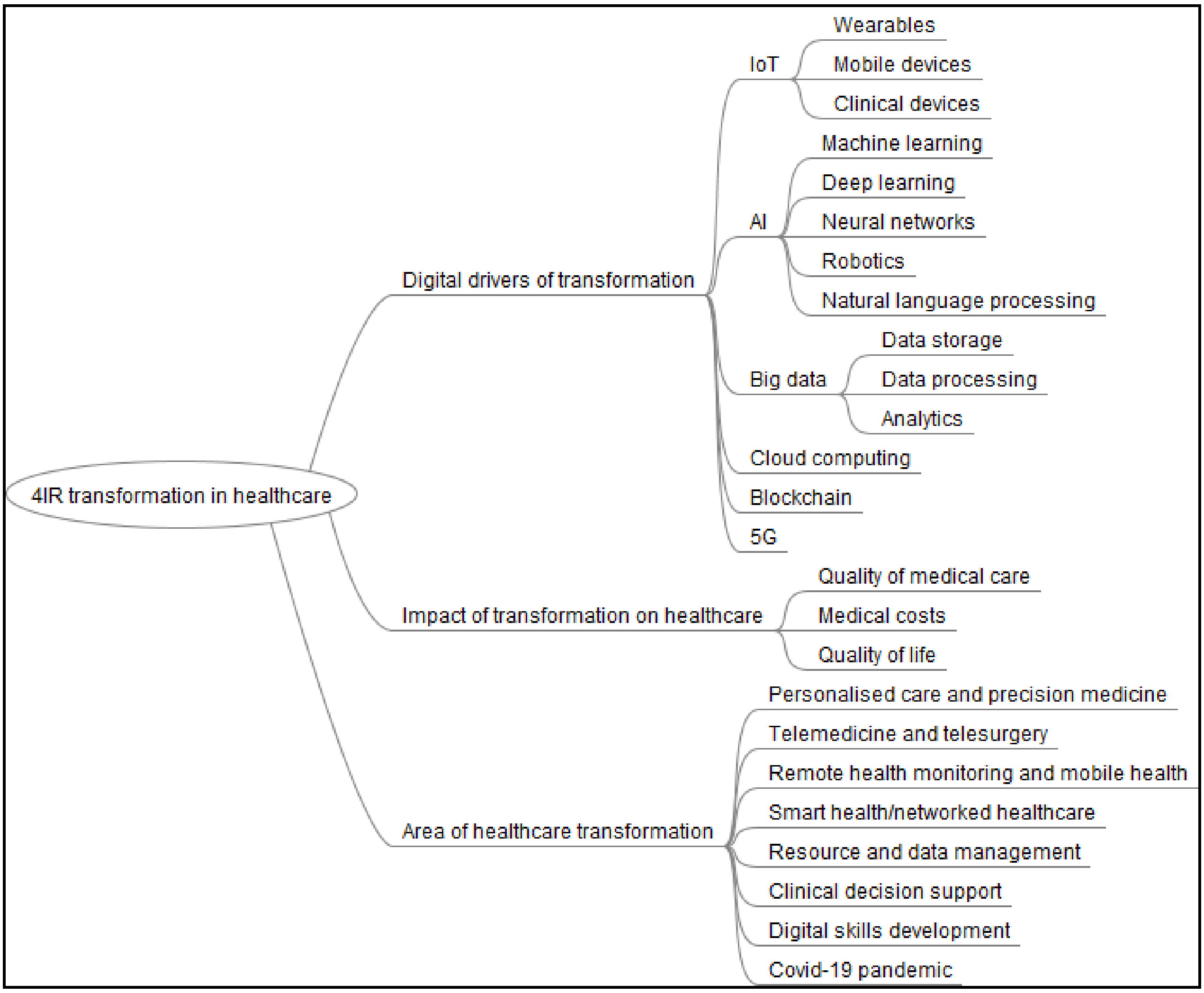

Figure 4.3: Themes for 4IR transformation in healthcare

4.2.1 Fourth Industrial Revolution technologies driving the digital transformation of healthcare

4.2.1.1 Artificial Intelligence

AI and other disruptive technologies are evolving through innovation from first-generation to next-generation technologies, mirroring the transformation of healthcare delivery, in pursuit of personalised care and population health (Alexander et al., 2019; McGrow, 2019; Wang & Alexander, 2020). The adoption of AI in healthcare is continuous with a mix of proven and potential applications in performing specific repeated tasks better than healthcare professionals (Alami et al., 2021; Arora, 2020; Lin et al., 2019).

The application of AI can support personalised care through pattern recognition, medical imaging, and classification of sensor data and EHR data for more accurate diagnostic and treatment outcomes (Alexander et al., 2019; Jheng, Kao, Yarmishyn, Chou, Hsu, Lin, Hu, Ho, Chen, Kao, Chen, & Hwang, 2020; Jin, Liu, Xu, Su, & Zhang, 2020; Noorbakhsh-Sabet, Zand, Zhang, & Abedi, 2019; Wang & Alexander, 2020). For example, the Viz.ai system in the United States of America in San Francisco, California, uses AI algorithms to diagnose stroke in Computerised Tomography (CT) scans and promptly notifies radiologists (Alexander et al., 2019).

Machine learning, a branch of AI that is based on data science and statistical modelling (Cosgriff et al., 2019), is used widely as a foundation for predictive clinical decision support in a learning healthcare system (Cosgriff et al., 2019; Noorbakhsh-Sabet et al., 2019). AI enhances big data through smart analysis algorithms that transform clinical data into actionable insights (Kang, Park, Cho, & Lee, 2018; Williams et al., 2018). For example, IBM's Watson for Oncology uses Natural Language Processing (NLP), a branch of AI, to read and interpret words, was used to make treatment recommendations from past clinical cases and clinical literature, with 93% concordance with physicians (Williams et al., 2018).

The application of AI has the potential to revolutionise and drastically alter the relationship between patients and healthcare providers through increased automation of routine healthcare tasks (Hazarika, 2020; Wang & Alexander, 2020). AI robots can improve the efficiency of medical services by automating the administrative tasks of nurses in hospitals and link medical staff to patient records in real-time (Lee & Yoon, 2021).

AI can also reform organisational structures and business processes for large organisations based on changes to both administrative and technical practices (Arora, 2020). The adoption of AI by healthcare providers depends on the priority of patient safety against cost and ethics considerations (Arora, 2020). For example, an upgrade to ICT infrastructure was necessary in the United Kingdom (UK) since existing infrastructure did not meet standards required for incorporating AI in the National Health Service (NHS) (Arora, 2020).

The second-generation AI applications, for example smart pills and speech recognition, are increasingly being adopted and are projected to reduce healthcare costs and improve quality of medical care (Ilan, 2021; Latif et al., 2021; Lin et al., 2019). Many potential AI applications are still at concept stage and not yet implemented in practice, especially infection control in health epidemiology (Wiens & Shenoy, 2018).

Nanotechnology, which incorporates AI, has over-promised but under-delivered so far, especially in providing solutions for cancer therapy. According to Germain, Caputo, Metcalfe, Tosi, Spring, Åslund, Pottier, Schiffelers, Ceccaldi, & Schmid (2020), new generation nanotechnology is slowly reaching implementation stage in healthcare (Germain, Caputo, Metcalfe, Tosi, Spring, Åslund, Pottier, Schiffelers, Ceccaldi, & Schmid, 2020). AI applications and nanotechnology are used to develop digital or smart pills that counter the waning effectiveness of chronic medication due to low adherence and loss of response to the medicines (Ilan, 2021). For example, one third of epilepsy patients develop drug resistance while a similar proportion with depression develops resistance to anti-depressants (Ilan, 2021).

Table 4.4 provides a summary of the research papers that focused on AI technologies, their transformation context and how they have been used to transform the healthcare system.

Table 4.4: AI-enabled transformation in healthcare

Author	AI application in healthcare	Transformation context
Alami, H., Lehoux, P., Denis, J. L., Motulsky, A., et al. (2021); Alexander, A., McGill, M., Tarasova, A., Ferreira, C., et al. (2019); Araiza-Garaygordobil, D., Jordán-Ríos, A., Sierra-Fernández, C., & Juárez-Orozco, L. E. (2020); Arora, A. (2020); Hazarika, I. (2020); Ilan, Y. (2021); Jheng, Y. C., Kao, C. L., Yarmishyn, A. A., Chou, Y.-B., et al. (2020); Lee, D., & Yoon, S. N. (2021); Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019); McGrow, K. (2019); Miotto, R., Wang, F., Wang, S., Jiang, X., et al. (2017); Scott, P., Dunscombe, R., Evans, D., Mukherjee, M., et al. (2018); Williams, A. M., Liu, Y., Regner, K. R., Jotterand, F., et al. (2018); Xu, J., Xue, K., & Zhang, K. (2019); Cai, Q., Wang, H., Li, Z., & Liu, X. (2019); Germain, M., Caputo, F., Metcalfe, S., Tosi, G., et al. (2020)	Diagnosis and treatment	• Healthcare delivery and expertise • Medical imaging • Health systems and digital medicine • Innovation in healthcare • Role of healthcare providers • Digital pills used to reduce healthcare costs • AI's transformative role in healthcare • Primary care • Precision medicine • Ophthalmology • Intelligent decision-making systems in healthcare
Bhattad, P. B., & Jain, V. (2020); Jin, X., Liu, C., Xu, T., Su, L., et al. (2020); Mansour, R. F., Amraoui, A. E., Nouaouri, I., Díaz, V. G., et al. (2021); Latif, S., Qadir, J., Qayyum, A., Usama, M., et al. (2020); Tobore, I., Li, J., Yuhang, L., Al-Handarish, Y., et al. (2019)	Remote health monitoring, diagnostics	• AI in healthcare • AI-biosensors • Disease diagnosis model for smart healthcare system • Speech technology • Healthcare delivery
Galmarini, C. M., & Lucius, M. (2020); Noorbakhsh-Sabet, N., Zand, R., Zhang, Y., & Abedi, V. (2019)	AI-assisted diagnosis, drug discovery and development, clinical decision-making	• The R&D model to AI collective intelligence to improve healthcare • AI-enabled decision support systems are transforming healthcare
Goldsack, J. C., & Zanetti, C. A. (2020)	Skills development	Transformation of healthcare
Meskó, B., Hetényi, G., & Győrffy, Z. (2018)	Resource management	Paradigm shift in the doctor-patient relationship.
Wiens, J., & Shenoy, E. S. (2018)	Disease prevention	Transformation of clinical data for healthcare epidemiology

4.2.1.2 Internet of Things

Healthcare institutions that have adopted IoT technologies to optimise operational efficiency gain an advantage over their competitors through better quality of service and optimal resource management (Ahad et al., 2020; Lee & Yoon, 2021). IoT technologies, through Medicine 4.0, are responsible for a paradigm shift in the interaction between patients, healthcare professionals and medical devices in the healthcare industry (Qadri et al., 2020). IoT applications and the huge amount of data produced from sensors in medical and everyday smart devices have transformed the healthcare system from conventional to digital (Nazir, Khan, Khan, Ali, García-Magariño, Atan, & Nawaz, 2020).

Mobile and wireless technologies have transformed healthcare delivery from centralised healthcare facilities to ubiquitous healthcare consistent with the availability of internet connectivity (Muhammed et al., 2018). Mobile devices can deliver networked healthcare services using multisource and interoperable personal health records (PHR) maintained and owned by patients. In practice, the vast majority of healthcare applications (EHRs, patients' wearable devices, sensors, etc.) are not interoperable and cannot share data. IoT technologies can facilitate the sharing of PHRs and sensor data with healthcare providers in order to improve diagnostic and treatment outcomes for patients (Hirose et al., 2020; Roehrs et al., 2017).

Revolutionary advances in IoT technologies are rapidly transforming healthcare from digital to intelligent as part of smart healthcare. The transformation includes smart hospital design for both in-patient and out-patient medical care and hospital management (Hejazi Dehaghani, Hajrahimi, & Dehaghani Hejazi, 2020; Rubí & Gondim, 2019; Uslu et al., 2020; Zheng et al., 2019). Smart healthcare provides real-time and on-demand healthcare services to patients anytime and from any location through IoT-enabled smart devices for better disease prevention, diagnosis and treatment outcomes (Kang et al., 2018; Kelly et al., 2020; Qadri et al., 2020).

AI-biosensors in IoT devices are transforming healthcare from being centralised, encounter-based, and reactive to a distributed, continuous, connected and proactive personalised care system (Kelly et al., 2020; Meinert et al., 2018). The transformation enables remote health monitoring, cloud-based diagnostics, and treatment at the point of care (POC) (Jin et al., 2020; Kukafka, 2019; Nasajpour, Pouriyeh, Parizi, Dorodchi, Valero, & Arabnia, 2020; Pathinarupothi et al., 2019). Interconnected medical IoT devices and smartphones use the Internet and other telecommunication infrastructure for real-time remote health monitoring and medical care (Jagadeeswari, Subramaniyaswamy, Logesh, & Vijayakumar, 2018; Mansour, Amraoui, Nouaouri, Díaz, Gupta, & Kumar, 2021; Rathore, Ahmad, Paul, Wan, & Zhang, 2016).

Cloud computing and distributed file systems provide the infrastructure for data management that is required for efficient sharing, storing and processing of healthcare big data in a secure environment (Wang & Alexander, 2020). Mobile cloud computing facilitates smart health monitoring through superior data management and real-time communication between patients and healthcare professionals (Aghdam et al., 2021; Kang et al., 2018; Muhammed et al., 2018). For example, IBM set up the Watson Health business unit to provide an open-source and secure cloud-based platform for analysis and interpretation of healthcare big data for better decision-making (Kang et al., 2018).

IoT applications in healthcare reduce the need for healthcare professionals to intervene as patients are more self-aware of their health status with focus on disease prevention (Kelly et al., 2020). Healthcare professionals benefit through better clinical decisions and increased knowledge in healthcare (Rubí & Gondim, 2019).

A summary of the research papers that focused on IoT technologies, their transformation context and how they have been used to transform the healthcare system is provided in Table 4.5.

Table 4.5: IoT-enabled transformation in healthcare

Author	**IoT application in healthcare**	**Transformation context**
Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021); Bayo-Monton, J. L., Martinez-Millana, A., Han, W., Fernandez-Llatas, C., et al. (2018); Coulby, G., Clear, A., Jones, O., Young, F., et al. (2020); Islam, M. M., Rahaman, A., & Islam,	Diagnosis, treatment and remote health monitoring	• Transformation of healthcare • Telemedicine • Biomedical engineering for personalised healthcare

Author	IoT application in healthcare	Transformation context
M. R. (2020); Javaid, M., & Khan, I. H. (2021); Greco, L., Percannella, G., Ritrovato, P., Tortorella, F., et al. (2020); Kang, M., Park, E., Cho, B. H., & Lee, K. S. (2018); Meinert, E., Van Velthoven, M., Brindley, D., Alturkistani, A., et al. (2018); Muhammed, T., Mehmood, R., Albeshri, A., & Katib, I. (2018); Nasajpour, M., Pouriyeh, S., Parizi, R. M., Dorodchi, M., et al. (2020); Pathinarupothi, R. K., Durga, P., & Rangan, E. S. (2019); Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., et al. (2020); Ramallo-González, A. P., González-Vidal, A., & Skarmeta, A. F. (2021); Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., et al. (2016); Rubí, J. N., & L Gondim, P. R. (2019); Sadoughi, F., Behmanesh, A., & Sayfouri, N. (2020); Kelly, J. T., Campbell, K. L., Gong, E., & Scuffham, P. (2020); Sartori, F. (2020); Singh, R. P., Javaid, M., Haleem, A., & Suman, R. (2020); Sriram, R. D., & Subrahmanian, E. (2020); Uslu, B. Ç., Okay, E., & Dursun, E. (2020); Yang, X., Wang, X., Li, X., Gu, D., et al. (2020); Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M. (2021); Zheng, X., Sun, S., Mukkamala, R. R., Vatrapu, R., et al. (2019); Avila, K., Sanmartin, P., Jabba, D., & Jimeno, M. (2017); Ahad, A., Tahir, M., Aman Sheikh, M., Ahmed, K. I., Mughees, A., & Numani, A. (2020)		• Smart health monitoring • Disruptive technologies in healthcare • Evolution of IoT based healthcare systems • Health monitoring system for smart health • Model of health care from encounter-based care through connected continuous care • Networked healthcare system • Personalized healthcare systems • H-IoT systems • Data management using cloud technology • Shifts health care from hospital to home; from specialist to generalist; and from treatment to prevention. Moving health care provision from a central, hospital-based model to a networked, distributed model • Internet of Medical Things integrated with EHRs • e-Health has decentralized healthcare services from healthcare centres to lateralized locations such as homes and workplaces • Mobile and wearables in healthcare • Tracking and tracing of infections • From digital to intelligent healthcare • Service oriented architecture for remote

Author	IoT application in healthcare	Transformation context
		patent monitoring • From the conventional specialist and hospital-focused style to a distributed patient-focused manner
Fischer, G. S., Righi, R. d. R., Costa, C. A. d., Galante, G., et al. (2019); Hejazi Dehaghani, S. A., Hajrahimi, B., & Dehaghani Hejazi, S. M. (2020); McNabb, T., Myers, T., Wicking, K., Lei, L., et al. (2018); Rathore, M. M., Ahmad, A., Paul, A., Wan, J., et al. (2016); Mieronkoski, R., Azimi, I., Rahmani, A. M., Aantaa, R., et al. (2017); Celesti, A., Ruggeri, A., Fazio, M., Galletta, A., et al. (2020); Uslu, B. Ç., Okay, E., & Dursun, E. (2020); Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M. (2021); Ahad, A., Tahir, M., Aman Sheikh, M., Ahmed, K. I., Mughees, A., & Numani, A. (2020); Park, A., Chang, H., & Lee, K. J. (2017)	Clinical Decision Support	• Human resource allocation • The advancement and development of this technology has added a new section to the field of health and treatment called digital health advisers • Health monitoring for emergency response • Nursing care • Tele-medical laboratory with blockchain technology for data security • Hospital's decision-making in a digital environment • Relief supply chain for Covid-19 pandemic • Asset management • Patient care in a hospital

4.2.1.3 Big data

Big data enables the collection, processing and analysis of multimodal biomedical data that is sourced from a variety of structured and unstructured data sets. Healthcare data is compatible with big data through biosensor data, genomics, clinical data, and health administration data (Lun, 2018). Big data analysis provides information for real-time smart healthcare decision-making using data mining and predictive analysis on health behaviour (Wang & Alexander, 2020). The multimodal healthcare data generated by IoT sensors and other clinical data is managed using big data tools for better prevention, diagnosis and treatment of diseases (Abdel-Basset, Chang, & Nabeeh, 2021; Rathore et al., 2016;

Tobore et al., 2019). Critical care medicine in the intensive care unit (ICU) relies on continuous monitoring of physiological data from interconnected devices that are used to generate clinical insights from big data in clinical decision support systems (Cosgriff et al., 2019; Vellido, Ribas, Morales, Ruiz Sanmartín, & Ruiz Rodríguez, 2018).

Big data implementation still faces challenges that limit its potential to further transform healthcare delivery (Cosgriff et al., 2019). The challenges include poor data quality, data governance, data ownership between competing healthcare providers, and transformation of unstructured and structured data to achieve interoperability (Bublitz, Oetomo, Sahu, Kuang, Fadrique, Velmovitsky, Nobrega, & Morita, 2019; Miotto et al., 2018; Wang & Alexander, 2020). Cross-border data sharing remains a major challenge due to bureaucratic and jurisdictional red tape, lack of collaboration and interoperable databases (Cosgriff et al., 2019; Wang & Alexander, 2020).

A summary of the research papers that focused on the transformational role of big data technologies, their transformation context and how they have been used to transform the healthcare system is provided in Table 4.6.

Table 4.6: Big data-enabled transformation in healthcare

Author	Big data application in healthcare	Transformation context
Au-Yong-Oliveira, M., Pesqueira, A., Sousa, M. J., Dal Mas, F., et al. (2021); Lun, K. C. (2018)	Skills development	• Data transformation • Data technology for health informatics
Chen, Y., Guzauskas, G. F., Gu, C., Wang, B. C., et al. (2016); Au-Yong-Oliveira, M., Pesqueira, A., Sousa, M. J., Dal Mas, F., et al. (2021); Cosgriff, C. V., Celi, L. A., & Stone, D. J. (2019); Hirose, J., Wakata, Y., Tagi, M., & Tamaki, Y. (2020); Orphanidou, C. (2019); Vellido, A., Ribas, V., Morales, C., Ruiz Sanmartín, A., et al. (2018); Wang, L., & Alexander, C. A. (2020); Nazir, S., Khan, S., Khan, H. U., Ali, S., et al. (2020)	Prediction (diagnostic or prognostic) models and treatment	• Optimized individual treatments can reduce costs • Healthcare delivery • Medical information systems • Advanced predictive analytics • Biology evolves from a wet laboratory- centred science to a data-driven endeavour • Transformation of unstructured health data

4.2.1.4 Fifth generation technology

Revolutionary 5G technologies are rapidly transforming healthcare (Ahad, Tahir, & Yau, 2019). 5G-enabled Augmented Reality (AR) and Virtual Reality (VR) have transformed healthcare through faster internet connections for interconnected medical devices for improved diagnosis, treatment, rehabilitation training and telemedicine (Abdel-Basset et al., 2021; Li, 2019; Qadri et al., 2020). 5G and IoT are vital for the attainment of next-generation smart healthcare as it addresses network and device limitations that hinder increased data transfer speeds (Aghdam et al., 2021; Ahad et al., 2020; Ahad et al., 2019; Muhammed et al., 2018).

5G technologies can increase network capacity and energy efficiency a thousand times and ten times, respectively which scales up the implementation of wearable devices and other mobile sensor devices (Qadri et al., 2020). Low latency and ultra-reliable internet communication is necessary for sensitive medical services including remote surgery (Ahad et al., 2020). 5G technologies such as Wireless Regional Area Networks (WRAN) also provide the capability to service remote and scarcely populated areas which make healthcare services more accessible (Ahad et al., 2020).

A summary of the research papers that focused on the transformational role of 5G-enabled technologies, their transformation context and how they have been used to transform the healthcare system is provided in Table 4.7.

Table 4.7: 5G-enabled transformation in healthcare

Author	5G application in healthcare	Transformation context
Ahad, A., Tahir, M., & Yau, K. L. (2019)	Remote patient monitoring, remote surgery, remote medical assistance, diagnostics	Data transfer using 5G and IoT applications in healthcare
Li, D. (2019)	Telemedicine, teleconsultation, and tele-surgery	Patient rehabilitation and telemedicine

4.2.1.5 Blockchain

In a networked healthcare system that is enabled by IoT technologies and distributed computing, blockchain applications improve the integration of data and validates the authenticity of transactions between multiple parties (Abdel-Basset et al., 2021; Qadri et al., 2020). Blockchain technology uses a decentralised distributed ledger to ensure medical data security and privacy for multisource data in patient-centric smart healthcare systems (Anjum, Rasid, Khalid, Alam, Daud, Abas, Sam, & Yusof, 2020; Kang et al., 2018).

Blockchain improves the transfer of medical information between patients and healthcare professionals in a secure environment (Alexander et al., 2019; Qadri et al., 2020). The fast-growing Blockchain facilitates the analysis and shared graphics processing for AI applications and enables patients to access their secure healthcare data from any location (Alexander et al., 2019). For example, blockchain technology secures patient data and guarantees integrity of healthcare decisions in a cloud-based tele-medical laboratory where tests are performed on patients in a hospital using interconnected devices and shared with other hospitals for validation and consultation (Celesti et al., 2020). A federation of hospitals use cloud infrastructure to gain economies of scale and improve their data management capabilities. This improves the quality of medical services and reduces medical and operational costs in a decentralised computing environment (Celesti et al., 2020).

A summary of the research papers that focused on the transformational role of Blockchain technologies, their transformation context and how they have been used to transform the healthcare system is provided in Table 4.8.

Table 4.8: Blockchain-enabled transformation in healthcare

Author	Blockchain application in healthcare	Transformation context
Anjum, H. F., Rasid, S. Z. A., Khalid, H., Alam, M. M., et al. (2020)	Decision support	Transformation of healthcare

Author	Blockchain application in healthcare	Transformation context
Dimitrov, D. V. (2016)	Patient-centric care	Shift from a conventional infrastructure to a health information technology (HIT)

Although many of the research papers included in the SLR focused on the use of specific 4IR technologies in the healthcare section, a number of them only addressed the transformation of healthcare by digital technologies in general. A summary of these studies is provided in Table 4.9.

Table 4.9: Digital technologies in healthcare

Author	Digital technologies application in healthcare	Transformation context
Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2020); Bublitz, F. M., Oetomo, A., Sahu, K. S., Kuang, A., et al. (2019); Castro, E. M., & Faria Araújo, N. M. (2020); Chute, C., & French, T. (2019); Erikainen, S., Pickersgill, M., Cunningham-Burley, S., & Chan, S. (2019); Huang, F., Brouqui, P., & Boudjema, S. (2021); Jagadeeswari, V., Subramaniyaswamy, V., Logesh, R., & Vijayakumar, V. (2018); Kukafka, R. (2019); Roehrs, A., da Costa, C. A., Righi, R. d. R., & de Oliveira, K. S. (2017); Vandenberg, O., Durand, G., Hallin, M., Diefenbach, A., et al. (2020); Yamin, M. (2018)	Remote health monitoring, diagnosis and surveillance	• Covid-19 related healthcare and disruptive technologies • Participatory medicine • Disease prevention and control • From hospital-centric care to personalized individual-centric services • Digitally engaged health consumer • Processing PHR data automatically and combining data from sensors with stored records for transformation into useful knowledge • Digital technologies for microbiologists • Healthcare management

Author	Digital technologies application in healthcare	Transformation context
Benis, A., Tamburis, O., Chronaki, C., & Moen, A. (2021)	Personalised care	The timely identification of health care customers, efficient service provision, and the continuous improvement of care quality accelerate the digital transformations of health care systems
Bublitz, F. M., Oetomo, A., Sahu, K. S., Kuang, A., et al. (2019)	Predicting hospital readmission	Disruptive technologies in healthcare
Chute, C., & French, T. (2019)	Smart hospitals and tele-medicine models	Progressive virtualization in order to enable the personalization of health and care next to real time for patients, professionals and formal and informal carers.

4.2.2 Healthcare transformation area

4.2.2.1 Personalised care and precision medicine

Cloud computing, IoT and big data applications contribute to the shift from hospital-centric medical services to patient-centric personalised medical services with better diagnostic and treatment outcomes (Araiza-Garaygordobil, Jordán-Ríos, Sierra-Fernández, & Juárez-Orozco, 2020; Goldsack & Zanetti, 2020; Jagadeeswari et al., 2018; Nasajpour et al., 2020; Williams et al., 2018). The revolution in low-latency video streaming, medical imaging and high data transmission speed from 5G technologies has transformed the traditional approach to diagnosis and treatment to self-determination medicine (Li, 2019).

Person-centred medicine gives more autonomy to a patient from clinical services in a patient-centric and participatory healthcare system offering an interactive diagnosis and treatment plan (Ahad et al., 2019; Araiza-Garaygordobil et al., 2020; Chen et al., 2016; Chute & French, 2019; Li, 2019). In participatory healthcare, individuals play a dual role of being patients and engaged participants and consumers in healthcare delivery and not as mere recipients of healthcare services (Alexander et al., 2019; Erikainen et al., 2019; Kang et al., 2018). IoT and AI applications use both in-hospital personalised devices and remote patient monitoring data to tailor clinical decisions to individual patient's needs, with improved diagnosis and treatment outcomes (Mieronkoski, Azimi, Rahmani, Aantaa, Terävä, Liljeberg, & Salanterä, 2017).

Medical data produced by both patients and healthcare providers in a digital and interconnected big data platform, enables individuals to be more in control of their own health (Alexander et al., 2019; Erikainen et al., 2019; Kang et al., 2018; Meinert et al., 2018). The choice of the most appropriate treatment is a joint decision between the patient and the healthcare professional (Chen et al., 2016).

Insights from big data and deep learning are used for preventive and predictive precision medicine, clinical decision support and critical care to ensure the right disease diagnostics and treatment for the right person at the right time (Chen et al., 2016; Cosgriff et al., 2019; Huang, Brouqui, & Boudjema, 2021; Miotto et al., 2018; Orphanidou, 2019; Wang & Alexander, 2020). Deep learning can identify patterns in clinical data images, EHRs, genomics, and sensor data from smartphones and other wearable devices for improved individualised diagnostics and treatment (Castro & Faria Araújo, 2020; Miotto et al., 2018). Precision medicine benefits from 5G technology which resolves the challenges of low data transfer speeds, that is, bandwidth, data transmission speed and latency (Li, 2019).

However, despite the benefits or personalised care and precision medicine, the amount of responsibility transferred from the government to individual patients has been ethically criticised for reducing government accountability and promoting unequal access to medical care through the "digital divide" (Erikainen et al., 2019).

4.2.2.2 Telemedicine and telesurgery

High data transfer speeds from 5G technology enable real-time interactive experience in telemedicine when patients are connected to cloud computing platforms (Ahad et al., 2019; Li, 2019). AI, IoT and other 4IR technologies are the cornerstone of modern networked healthcare systems (Rosen, Kun, Mosher, Grigg, Merrell, Macedonia, Klaudt-Moreau, Price-Smith, & Geiling, 2016). They are used in most parts of healthcare including in telemedicine for virtual clinical guidance of patients by healthcare professionals (Mansour et al., 2021; Rosen et al., 2016; Wang & Alexander, 2020).

Machine learning and deep learning AI applications provide high-precision, controllable and flexible robotic-assisted surgery that enables surgeons to perform complex and less invasive operations remotely and at the point of care (Alexander et al., 2019; Castro & Faria Araújo, 2020; Lee & Yoon, 2021; Qadri et al., 2020; Yamin, 2018). VR, AR and Mixed Reality (MR) use robotic surgery for the training of surgeons using simulators without compromising patient safety and operating time (Yamin, 2018).

4.2.2.3 Remote health monitoring and mobile health

Big data, cloud computing and mobile telephone networks enable medical IoT devices and smartphones with healthcare applications to provide real-time remote health monitoring in a remote healthcare system (Dimitrov, 2016; Huang et al., 2021; Islam, Rahaman, & Islam, 2020; Jagadeeswari et al., 2018; Miotto et al., 2018; Pathinarupothi et al., 2019; Rosen et al., 2016; Tobore et al., 2019; Wang & Alexander, 2020; Yang, Wang, Li, Gu, Liang, Li, Zhang, & Zhong, 2020). 5G has improved remote health monitoring of patients, remote surgery, and optimal allocation of medical resources through high data transfer speeds (Li, 2019).

AI and IoT applications conduct real-time remote health monitoring by analysing physiological big data generated by sensors in wearable devices and reduces hospital readmissions and emergency room visits (Avila et al., 2017; Latif et al., 2021; Lee & Yoon, 2021; Lin et al., 2019). A real-time emergency response system uses IoT and Big data technologies for remote health monitoring and rapid response to medical emergencies including infections and complications in rehabilitation systems (Greco, Percannella, Ritrovato, Tortorella, & Vento, 2020; Mieronkoski et al., 2017; Rathore et al., 2016).

Remote health monitoring is also used for tracking the physical movements of patients and healthcare professionals in hospital surroundings, the distribution of medicines and activities of daily living such as sleep detection and fall monitoring (Fischer, Righi, Costa, Galante, & Griebler, 2019; Mieronkoski et al., 2017). Infection control measures in hospitals also use remote monitoring of healthcare professionals to ensure adherence to hygiene procedures (Mieronkoski et al., 2017). IoT applications are used for diagnosis, treatment, track-and-trace, as well as prevention and control of epidemic diseases (Greco et al., 2020). For example, in Eunpyeong St. Mary's Hospital of the Catholic University of Korea, two robots were used to accompany healthcare professionals to in-patient rooms and to accompany patients around some areas within the hospital (Lee & Yoon, 2021).

A negative aspect of remote health monitoring relates to the use of invasive biosensors, such as penetrative needles (Kang et al., 2018). This has the potential to reduce the quality of medical care and adherence to treatment and has necessitated the introduction of non-invasive sensors for improved health outcomes (Kang et al., 2018). Remote patient monitoring through non-invasive sensors includes wearable electrochemical sensors that use biomarkers in sweat and saliva (Kang et al., 2018; Mieronkoski et al., 2017). Speech recognition technology and voice-enabled technologies can be used for remote health monitoring of patients in a 5G-enabled mobile network to determine distress levels while preserving patients' privacy (Latif et al., 2021).

IoT-based expert systems that are connected to wearable devices using mobile devices connected to cloud services are applied in mHealth even though they are still generally underutilised in healthcare (Tobore et al., 2019). Smartphones with sensors and wearable technologies promote healthy lifestyles through physiological monitoring for improved diagnosis, treatment of chronic diseases, and home-based rehabilitation (Miotto et al., 2018; Roehrs et al., 2017; Sadoughi, Behmanesh, & Sayfouri, 2020; Sartori, 2020).

Mobile devices can also be used for education and empowerment of patients for better self-care and coordination of healthcare delivery by healthcare professionals (Aghdam et al., 2021).

4.2.2.4 Smart health and networked healthcare

Smart or networked healthcare systems transform healthcare from the conventional centralised hospital setup run by healthcare professionals administering treatment (Rosen et al., 2016). With smart and networked healthcare, the conventional centralised healthcare system is replaced by a remote and networked home-based or community clinic system that is overseen by generalists and focused on diagnostics and disease prevention (Rosen et al., 2016). A smart data-driven and collaborative cloud-based healthcare system integrates an interactive clinical decision support system for intelligent decisions on tasks including consultation, triage, in-hospital and out-of-hospital diagnostics and treatment (Cai, Wang, Li, & Liu, 2019).

Smart healthcare facilitates remote health services at any time and from any geographic location to facilitate predictive and preventive personalised care (Aghdam et al., 2021; Kelly et al., 2020; Yamin, 2018). Smartphones fitted with medical sensors and medical software applications are becoming central to smart healthcare delivery (Ahad et al., 2020).

Smart healthcare optimises network resources and increases network efficiency as interconnected IoT devices produce high volumes of data and utilise more bandwidth. 5G technologies meet the data transfer requirements for smart healthcare (Ahad et al., 2020; Ahad et al., 2019). A 5G-based smart healthcare network can be achieved through advancements in mobile broadband, machine-to-machine communications, more reliable and low latency communication and the WRAN (Ahad et al., 2020).

4.2.2.5 Resource and data management

5G-enabled smart healthcare and AI applications can mitigate against the unequal distribution of medical resources between well-resourced urban areas and under-resourced rural areas (Li, 2019; Rosen et al., 2016; Xu et al., 2019). IoT applications provide an intelligent network of everyday smart devices that can lead to the optimal use of hospital resources under a smart hospital design for improved organisational performance (Ahad et al., 2020; Hejazi Dehaghani et al., 2020; Javaid & Khan, 2021; Uslu et al., 2020). Big data can optimise resource allocation in healthcare through precision medicine and the direction of patients to facilities where care is available (Sriram & Subrahmanian, 2020; Wang & Alexander, 2020). Data-driven healthcare improves competitive advantage for healthcare providers through efficient processes and optimised resource management (Lun, 2018).

There is increasing “datafication” of healthcare delivery where more medical data is collected by individuals through self-monitoring devices and healthcare providers adopt data-driven decision making (Erikainen et al., 2019). In-hospital data sources are generally not suitable for medical expert systems that provide intelligent diagnosis and treatment decisions for increased incidents of chronic diseases and high number of the aging population (Cai et al., 2019). IoT applications in healthcare facilities automate the collection and processing of healthcare data using low cost sensors and devices that is imported into EHRs (Aghdam et al., 2021; Meinert et al., 2018; Mieronkoski et al., 2017).

Medical devices and wearables produce high volumes of diverse and complex healthcare data that requires big data analytics and cloud computing to modify, manage and analyse for better insights (Jagadeeswari et al., 2018; Nazir et al., 2020). Healthcare systems generate multimodal and multisource data that is usually unintegrated and does not support interactive decision support for better diagnosis and treatment outcomes (Cai et al., 2019; Vellido et al., 2018). A data store made of an integrated data structure with interoperability provides meaningful insights from AI applications (Dimitrov, 2016).

Big data infrastructure can be used in a smart healthcare system to collect, store, process and analyse large volumes of data from medical IoT devices and smartphones (Au-Yong-Oliveira, Pesqueira, Sousa, Dal Mas, & Soliman, 2021). Big data insights are used for disease prevention, early diagnosis to improve patient quality of life and reduce preventable deaths (Cai et al., 2019; Jagadeeswari et al., 2018; Yamin, 2018). Cloud computing supports big data with distributed computing that enables storage, processing and retrieval of medical data from any location for telemedicine over the Internet (Jagadeeswari et al., 2018).

4.2.2.6 Clinical decision support systems

Hospitals use big data and Natural Language Processing (NLP) tools to provide clinicians and managers with decision support on surveillance and operational insights to improve operational efficiency (Fischer et al., 2019; Orphanidou, 2019). The use of IoT technologies with smart devices in a networked and intelligent healthcare system can provide rapid and accurate insights from a distributed computing environment for smart decision making for patients and resource management (Pathinarupothi et al., 2019; Uslu et al., 2020). Virtual nursing assistants using smart algorithms can perform repetitive tasks, such as responding to medical questions and reminding patients about their daily routines, medication schedules and appointments (Lee & Yoon, 2021).

Smart AI technologies provide innovations with the potential to transform the prevention, prediction, diagnosis and treatment of diseases (Lin et al., 2019). AI applications complement the decisions made by healthcare professionals in their diagnosis and treatment by using virtual patient representations in integrated EHRs and other patient data for personalised care (Galmarini & Lucius, 2020). However, it is important that healthcare professionals guard against automation bias where they over-rely on the “black box” smart technologies at the expense of their own judgement (Arora, 2020).

Smart algorithms can diagnose some diseases and match or outperform well-trained healthcare professionals, for example skin cancer diagnosis, through pattern analysis of medical images (Galmarini & Lucius, 2020; Lee & Yoon, 2021; Williams et al., 2018; Xu et al., 2019). AI applications can also detect non-evident patterns in clinical data that may indicate potential health complications that require urgent interventions (Galmarini & Lucius, 2020).

Errors in diagnostics make up the majority of medical errors (Hazarika, 2020; Lee & Yoon, 2021; Rubí & Gondim, 2019). AI reduces medical errors which improves clinical decision making by professionals, as well as patient satisfaction through increase self-awareness of their health status and reduced intervention by health professionals (Hazarika, 2020; Lee & Yoon, 2021; Rubí & Gondim, 2019). Smart algorithms provide predictive analysis from digital medical records and enable seamless communication between patients, their relatives, and healthcare professionals in hospitals which improves operational efficiency (Lee & Yoon, 2021).

4.2.2.7 Digital skills development for healthcare professionals

Healthcare professionals also require the transformation of how they acquire their skills to handle the paradigm shift due to the evolving AI applications that are continuously transforming healthcare delivery to predictive and preventive personalised care (Au-Yong-Oliveira et al., 2021; McGrow, 2019). Disruptive technologies in healthcare have brought about evolutionary and revolutionary transformation that may help address the shortage and distribution of healthcare workers (Hazarika, 2020). However, the implementation of digital technologies also creates a digital skills gap that hinders the pace of transformation in a digitally-driven healthcare system (Goldsack & Zanetti, 2020).

The automation of healthcare activities with increased productivity may lead to redundant healthcare jobs (Hazarika, 2020). The growing proliferation of disruptive technologies in healthcare requires an extended curriculum for healthcare professionals that includes proficiency in expert systems and data science in a patient-centric healthcare system (Cosgriff et al., 2019; Goldsack & Zanetti, 2020; Hazarika, 2020; Xu et al., 2019).

A data-driven healthcare system requires healthcare providers to have in-sourced inter-professional analytics skills supported by comprehensive data governance policies and standards (Au-Yong-Oliveira et al., 2021; Lun, 2018). Technical skills, including cyber security experts, data scientists and data engineers to protect healthcare ICT infrastructure against cyber-attacks, should be recruited into the healthcare industry (Goldsack & Zanetti, 2020).

4.2.2.8 The role of Fourth Industrial Revolution Technologies during the Covid-19 pandemic

The Covid-19 pandemic has led to increasing demand for networked IoT-enabled healthcare due to the urgent need for remote health monitoring and advanced information system for physiological patient data (Benis, Tamburis, Chronaki, & Moen, 2021; Javaid & Khan, 2021; Nasajpour et al., 2020). The pandemic has reduced regulatory barriers to the adoption of digital healthcare delivery as it closed traditional contact-based healthcare to virtual and remote medical services (Kelly et al., 2020).

At the height of the pandemic, smart disruptive technologies, such as AI and IoT, were used by public health institutions to prevent and predict Covid-19 outbreaks, to track, trace and monitor patients affected by the disease from early diagnosis, during quarantine and after they have recovered (Huang et al., 2021; Nasajpour et al., 2020; Ramallo-González, González-Vidal, & Skarmeta, 2021; Singh, Javaid, Haleem, & Suman, 2020). An IoT-enabled supply chain management (SCM) approach is used to identify potential Covid-19 cases, procure medical supplies and provide patient transport to healthcare facilities (Zahedi, Salehi-Amiri, Smith, & Hajiaghaei-Keshteli, 2021). 4IR applications provide more accurate 5G-enabled real-time diagnosis and treatment outcomes from data sources integrated through Blockchain technology and analysed using big data (Abdel-Basset et al., 2021).

Disruptions in operations and human errors during the outbreak of the Covid-19 pandemic make it difficult to control the spread of the virus within hospital management systems (Uslu et al., 2020). Smart hospitals use IoT infrastructure for Covid-19 infection control at a local global scale through minimisation of human-human contact.

4.2.3 Impact of digital transformation in healthcare

4.2.3.1 High quality medical care

5G technology can improve the quality of medical care and patient experience through minimisation of medical errors and improved efficiency (Ahad et al., 2019; Li, 2019). IoT technologies improve Quality of Service (QoS) by offering intelligent capabilities in networked expert systems that allow for integrated, rapid and continuous transfer of healthcare information between patients and healthcare professionals (Ahad et al., 2020; Nasajpour et al., 2020; Qadri et al., 2020; Rosen et al., 2016; Uslu et al., 2020). 5G and other next-generation telecommunication technologies increase patient access to information and the quality medical care through personalised diagnostics and treatment (Araiza-Garaygordobil et al., 2020; Sriram & Subrahmanian, 2020). Networked healthcare can increase the performance of healthcare providers, enabling them to deliver efficient, effective, and high-quality medical care (Hazarika, 2020; Qadri et al., 2020; Rosen et al., 2016; Sadoughi et al., 2020; Xu et al., 2019).

Despite the potential of digital transformation to improve the quality of healthcare, questions still remain on the scale and nature of the impact of AI on healthcare beyond the diagnosis and treatment of disease. However, these questions have not slowed down the innovation of AI applications to improve quality of healthcare services and reduce costs (Lee & Yoon, 2021; Vandenberg et al., 2020).

4.2.3.2 Reduction of medical costs

Health economics and outcomes research (HEOR) examines the costs, cost-effectiveness and economic value of using digital technologies in precision medicine (Chen et al., 2016). Precision medicine, through a precision HEOR, reduces medical costs through optimised individual treatments by eliminating the experience of trying different less successful treatments (Chen et al., 2016). The manufacturers of medicines and medical devices can save costs by quickly identifying target and scarce patient populations from real-world data without expensive and lengthy clinical trials (Chen et al., 2016).

Remote health monitoring through smartphones with healthcare applications enables cost-effective personalised treatment from cheaper IoT applications, cloud computing and higher data transmission speed (Coulby, Clear, Jones, Young, Stuart, & Godfrey, 2020; Dimitrov, 2016; Jagadeeswari et al., 2018; Latif et al., 2021; Nasajpour et al., 2020; Sadoughi et al., 2020). Big data and deep learning provide cost effective decision-making in clinical decision support systems for improved diagnosis and patient monitoring (Orphanidou, 2019; Wang & Alexander, 2020).

Smart algorithms such as data mining and deep learning facilitate data management and the extraction of insights from healthcare big data to achieve high quality medical care and cost reduction for clinical services (McGrow, 2019; Nazir et al., 2020; Wang & Alexander, 2020; Xu et al., 2019). 5G, AI and IoT are transforming healthcare through smart healthcare by reducing medical costs by empowering both patients and healthcare professionals and minimising costly face-to-face consultations (Araiza-Garaygordobil et al., 2020; Dimitrov, 2016; Li, 2019; Lin et al., 2019; Rubí & Gondim, 2019). New technologies reduce the cost burden from the diagnosis and treatment of chronic diseases through improved adherence and response to current medicines by patients (Aghdam et al., 2021; Ilan, 2021; Latif et al., 2021).

The networked healthcare model uses a cost-effective distributed network that integrates various 4IR technologies to achieve improved diagnosis, and treatment outcomes, as well as increased access to healthcare services (Aghdam et al., 2021; Castro & Faria Araújo, 2020; Rosen et al., 2016; Zahedi et al., 2021). IoT technologies and bioinformatics in a networked healthcare system can improve organisational performance for healthcare providers by reducing inefficiencies and controlling operational costs through automation and reduced communication costs (Aghdam et al., 2021; Ahad et al., 2020; Hejazi Dehaghani et al., 2020; Kelly et al., 2020; Lun, 2018).

Healthcare providers can use IoT technologies and sensor data to optimise clinical resources such as the occupancy and usage of clinical spaces (McNabb et al., 2018). The optimisation of clinical spaces reduces operational costs by reducing the maintenance costs of clinical assets and slowing down the growth of capital expenditure on healthcare infrastructure. An efficient healthcare system provides medical care to more patients and reduces the time they spend in healthcare facilities (McNabb et al., 2018).

4.2.3.3 Improved quality of life

IoT applications used for managing medication for patients can lead to improved treatment outcomes and consequent quality of life (Aghdam et al., 2021; Dimitrov, 2016). Non-invasive biosensors provide alternatives to invasive procedures such as blood tests and promotes adherence to treatment and improve patients' quality of life (Kang et al., 2018). Real-time, predictive, preventive remote health monitoring of patients in assistive health facilities improves their quality of life (Qadri et al., 2020).

AI applications free up healthcare professionals' time, thereby allowing them to focus on complex care since patients can obtain treatment advice for common symptoms through telemedicine. This improves their work-life balance and reduces burnout for healthcare professionals as they focus more on personalised care and less on administrative tasks (Lin et al., 2019).

4.3 CONCLUSION

A quantitative analysis of the SLR articles in section 4.1 showed that 47 out of the 84 articles were sourced from PubMed Central. The majority of the articles (58) were qualitative. The highest number of articles (32) were published in 2020 and the IoT had the highest number of articles at 30. Section 4.2 looked into the transformational role of 4iR technologies in healthcare and identified three main themes: 1) 4IR technologies driving transformation in healthcare, 2) digital transformation areas in healthcare, and 3) impact of digital transformation in healthcare. The top 3 individual technologies driving healthcare transformation are shown in Section 4.2.1 as IoT, AI and Big data.

Section 4.2.2 showed the areas of healthcare transformation include personalised care, precision medicine, telemedicine, remote health monitoring, mobile health, smart networked healthcare, data management, resource management, and clinical decision support systems. Section 4.2.3 showed the impact of digital transformation was identified in reduced medical costs for patients and healthcare providers, improved quality of medical care for patients, and improved quality of life for patients and healthcare professionals.

5 CONCLUSION

5.1 INTRODUCTION

This chapter summarises the research findings with the aim of highlighting how the main research and sub-research questions were answered in the mini-dissertation. Section 5.2 provides a summary of the chapters of the mini-dissertation. In section 5.3, the main research and sub-research questions are linked to the research findings to illustrate the extent to which they were answered. Section 5.4 outlines the limitations of the research and makes suggestions for future research. Section 5.5 provides the contribution of the study and section 5.6 outlines the final conclusion for the mini-dissertation.

5.2 OVERVIEW OF THE MINI-DISSERTATION

The mini-dissertation consists of five chapters. The introduction to the research study is given in Chapter 1. The chapter also includes the research context, purpose of the study, problem statement, research question and sub-questions, research objectives, scope, and the significance of the study. Chapter 2 provides an overview of extant literature that are relevant to the study. It includes brief discussions on the nature and extent of the transformation of healthcare by 4IR technologies, the application of digital technologies in healthcare, as well as the current opportunities and challenges for 4IR in healthcare.

Chapter 3 outlines the design of the SLR research process, including research paradigm applicable relevant to the study. Detailed discussions of the research results using both quantitative and qualitative methods were provided in Chapter 4. Chapter 5 provides a mapping of the key findings to the main research question and sub-questions. The chapter also highlights the limitations of the research and provided recommendations for further research.

5.3 SUMMARY OF THE RESEARCH FINDINGS

The main objective of the research was to explore the nature and extent of the transformation of healthcare by the 4IR. The main research question was answered through consolidated answers to the three research sub-questions in sections 5.3.1 to 5.3.3.

5.3.1 Research sub-question one

This research sub-question sought to determine the dominant applications of 4IR technologies in healthcare. The study determined the key 4IR technologies, their nature, extent, and types of digital transformation in healthcare. The medical fields affected by the digital transformation were also identified. The discussion showed that there are several complementary linkages between the technologies as they are mostly implemented in an integrated data-driven healthcare system.

As discussed in section 4.2.1, the key 4IR technologies that are driving the transformation of healthcare are AI, IoT, Big data, 5G, and Blockchain. These technologies complement each other across the data management and processing cycle. AI smart algorithms identify meaningful patterns in structured, unstructured, multisource and multimodal healthcare big data, including sensor data from IoT-enabled medical devices, wearables and mobile devices (Alexander et al., 2019; Jheng et al., 2020; Jin et al., 2020; Noorbakhsh-Sabet et al., 2019; Wang & Alexander, 2020). Cloud computing, 5G and Blockchain facilitate the distributed storage and processing of data from remote servers to enable real-time decision-making and anytime, anywhere medical services (Anjum et al., 2020; Kang et al., 2018).

The transformation of healthcare by the 4IR is through evolutionary, revolutionary, and disruptive technologies. Table 5.1 highlights the comparison between traditional healthcare delivery and transformed the transformed healthcare.

Table 5.1: Transformation of healthcare

Traditional healthcare	Transformed healthcare
Conventional paper-based	Digital and intelligent
Centralised	Decentralised and distributed
Reactive	Proactive

Traditional healthcare	Transformed healthcare
Treatment of disease	Preventive and predictive
Encounter-based	Continuous and “24/7”
Fixed geographic location	Remote services
Hospital-centric and generalised	Patient centric and personalised

The main areas of digital transformation in healthcare were discussed in section 4.2.2 and summarised in the following paragraphs.

Personalised care and precision medicine: Personalised care and precision medicine marked a significant paradigm shift from the conventional hospital-centric healthcare to patient-centric participatory healthcare (Ahad et al., 2019; Araiza-Garaygordobil et al., 2020; Chen et al., 2016; Chute & French, 2019; Li, 2019) where patients have more control in the management of their health conditions (Alexander et al., 2019; Erikainen et al., 2019; Kang et al., 2018; Meinert et al., 2018). 4IR applications enable an interactive diagnosis and treatment plan where patients participate in healthcare delivery and treatment decisions are taken jointly by patients and healthcare professionals (Chen et al., 2016). Personalised care and precision medicine tailor medical services for individuals leading to reduced costs, improved patient experience, and improved quality of life.

Telemedicine and telesurgery: Cloud computing platforms and 5G technology provide real-time interactive experience from high data transfer speeds in a networked healthcare system (Ahad et al., 2019; Li, 2019). Healthcare professionals are able to provide virtual clinical services to patients including remote clinical guidance (Mansour et al., 2021; Rosen et al., 2016; Wang & Alexander, 2020).

Robotics and smart algorithms are used to perform high-precision robotic-assisted surgery and remote operations by surgeons and at the point of care (Alexander et al., 2019; Castro & Faria Araújo, 2020; Lee & Yoon, 2021; Qadri et al., 2020; Yamin, 2018). Training of surgeons using simulators for robotic surgery is based on VR, AR and MR technologies underpinned by high speed data transfer in a networked healthcare system (Yamin, 2018).

Remote health monitoring and mobile health: Remote health monitoring is the cornerstone of a networked and remote healthcare system, mobile health, and the attainment of personalised care (Dimitrov, 2016; Huang et al., 2021; Islam et al., 2020; Jagadeeswari et al., 2018; Miotto et al., 2018; Pathinarupothi et al., 2019; Rosen et al., 2016; Tobore et al., 2019; Wang & Alexander, 2020; Yang et al., 2020). Remote healthcare systems and personalised care ultimately reduce medical costs, improve quality of medical care and quality of life through the use of non-invasive biosensors (Kang et al., 2018; Mieronkoski et al., 2017). Remote health monitoring is used within healthcare facilities for tracking of both patients and healthcare professionals to improve operational efficiencies and infection control within hospital surroundings (Fischer et al., 2019; Mieronkoski et al., 2017).

Cloud computing and smart mobile devices with healthcare applications enable wearable technologies and smartphones to collect physiological data for improved diagnosis, treatment and home-based rehabilitation (Miotto et al., 2018; Roehrs et al., 2017; Sadoughi et al., 2020; Sartori, 2020). Mobile health promotes personalised care with better self-care for patients and administration of healthcare delivery by healthcare professionals (Aghdam et al., 2021).

Smart health or networked healthcare: smart or networked healthcare systems provide a remote and home-based community clinic system that utilises remote health monitoring for better diagnostics and disease prevention (Rosen et al., 2016). Smart healthcare requires an optimised telecommunication network with higher data transfer speeds and low latency from 5G technology (Ahad et al., 2020; Ahad et al., 2019).

Resource and data management: 4IR technologies are used to optimise resource allocation within healthcare facilities and to mitigate against disparities in the allocation of medical resources between rural and urban areas (Li, 2019; Rosen et al., 2016; Xu et al., 2019). Efficient resource allocation facilitates precision medicine and improves organisational performance under a smart hospital design (Sriram & Subrahmanian, 2020; Wang & Alexander, 2020). Optimised resource management has direct impact on improved quality of medical care, reduced medical costs, and improved quality of life for patients, healthcare professionals, and healthcare providers.

The first frontier for transformation of healthcare entailed the shift from paper-based health records to digital health records, with particular focus on building data-driven healthcare systems that run on healthcare information systems (Erikainen et al., 2019). The healthcare industry generates high volumes of heterogeneous multisource and multimodal medical data that requires big data analysis for improved insights (Jagadeeswari et al., 2018; Nazir et al., 2020). IoT, AI and Big data technologies provide the infrastructure for data management from gathering, storage, retrieval, processing, and analysis within a secure data environment (Au-Yong-Oliveira et al., 2021). Next-generation technologies are transforming healthcare from digital to intelligent for real-time and accurate decision making that improves diagnostic, treatment and operational efficiency (Lun, 2018).

Clinical decision support: Clinical decision support systems use smart algorithms, EHRs, and sophisticated data analysis tools to improve diagnostic and treatment outcomes from clinical data, with focus on prevention and prediction of diseases (Lin et al., 2019). These systems also improve operational efficiencies and optimise resource management by automating repetitive tasks for healthcare professionals (Lee & Yoon, 2021) resulting in a reduced workload (Hazarika, 2020; Lee & Yoon, 2021; Rubí & Gondim, 2019).

Digital skills development: New technologies mitigate against the shortage of healthcare professionals and the unequal distribution of medical resources between rural and urban areas (Hazarika, 2020). Digital healthcare requires improved technology skills amongst healthcare professionals (Goldsack & Zanetti, 2020) which also reduces their opposition to the technologies. Automation of repetitive tasks using digital technologies can also lead to redundant healthcare professionals and that may also lead to resistance against digital applications in healthcare (Cosgriff et al., 2019; Goldsack & Zanetti, 2020; Hazarika, 2020; Xu et al., 2019).

5.3.2 Research sub-question two

The aim of research sub-question two was to determine the impact of 4IR technologies on the delivery of healthcare. As discussed in section 4.2.3, the impact of a smart networked healthcare system is evident in benefits to patients, healthcare professionals and healthcare providers. The following paragraphs summarise the impact of digital transformation on healthcare.

Quality of medical care: Healthcare professionals benefit through improved clinical decision support and remote patient monitoring that leads to improved diagnostic and treatment outcomes (Ahad et al., 2020; Nasajpour et al., 2020; Qadri et al., 2020; Rosen et al., 2016; Uslu et al., 2020). Healthcare providers are able to gain a competitive advantage through efficient operations and optimised resource management that leads to better quality of medical care (Hazarika, 2020; Qadri et al., 2020; Rosen et al., 2016; Sadoughi et al., 2020; Xu et al., 2019).

Medical costs: Precision medicine saves costs for patients as they do not need to experience less-than-optimal healthcare before a treatment that is tailored to the individual is identified (Chen et al., 2016). Remote health monitoring reduces transportation and face-to-face consultation costs especially in remote areas as patients do not need to travel to big cities for medical care (Araiza-Garaygordobil et al., 2020; Dimitrov, 2016; Li, 2019; Lin et al., 2019; Rubí & Gondim, 2019). The costs of the development of medicines and medical devices are reduced through the use of real-world data for scarce populations in place of expensive clinical trials (Chen et al., 2016).

4IR technologies also facilitate improved adherence to medical treatment, thereby leading to the efficacy of medicines and ultimately cost reduction (Aghdam et al., 2021; Ilan, 2021; Latif et al., 2021). Healthcare providers use new technologies to reduce operational and maintenance costs through optimisation of clinical resources (McNabb et al., 2018). Efficient healthcare systems serve more patients at lower cost (McNabb et al., 2018).

Quality of life: Patients gain more control of their health status (Kelly et al., 2020), can access medical services anytime and anywhere (Anjum et al., 2020; Kang et al., 2018), and this improves their quality of life. Healthcare professionals also benefit from improved quality of life due to a reduced workload as technology complements them through automation of repetitive tasks and real-time decision-making (Lin et al., 2019).

5.3.3 Research sub-question three

The objective of the third research sub-question was to determine how the Covid-19 pandemic accelerated digital transformation in healthcare. As discussed in section 4.2.2, the Covid-19 pandemic has accelerated the uptake of digital technologies in healthcare due to the urgent need for remote health monitoring (Benis et al., 2021; Javaid & Khan, 2021; Nasajpour et al., 2020). Infection control measures use digital technologies to identify potential Covid-19 cases, manage the procurement of medical supplies and patient transfer to medical facilities (Zahedi et al., 2021). Remote health monitoring employed disruptive technologies to prevent and predict Covid-19 outbreaks at the height of the pandemic. These technologies were also used to track, trace and monitor patients affected by the disease from early diagnosis, during quarantine and after they have recovered (Huang et al., 2021; Nasajpour et al., 2020; Ramallo-González et al., 2021; Singh et al., 2020).

5.3.4 Main research question

The objective of the main research question was to determine how the 4IR is transforming healthcare. The impact of the digital transformation of healthcare is evident in the quality of medical care, medical costs for patients and healthcare providers, and quality of life for both patients and healthcare professionals. Healthcare providers gain a competitive advantage due to optimised operations and resource management. Efficient healthcare systems are continuously accessible to more patients regardless of geographic location and provide cheaper, high quality medical services.

5.4 LIMITATIONS OF THE STUDY AND RECOMMENDATIONS FOR FUTURE RESEARCH

5.4.1 Limitations of the study

The limitations of the study are due to its research design and the inherent weaknesses of SLRs. The measurement of the quality of studies included in the SLR is difficult, subjective and has a significant risk of study and publication bias that may be reflected in the inclusion and exclusion criteria (Siddaway et al., 2019). Unpublished work and grey literature may be incorrectly classified as poor quality and published work does not always guarantee good quality studies (Siddaway et al., 2019).

5.4.2 Recommendations for future research

As indicated by Aceto et al. (2018), there is fragmentation in the literature on the transformation of healthcare by the 4IR Studies of this topic have shown varying conclusions on the impact of digital health on the rising costs of healthcare, improvement in the quality of life for patients and healthcare professionals (Tortorella et al., 2020). More studies are required with focus on the following areas:

- Distinguishing between the transformations of healthcare from actual implementation of digital technologies at scale compared to proof-of-concept studies.
- Studies that use elaborate methods to measure the economic cost of digital technologies to accurately reflect reductions in cost, taking into account expensive early adoption costs of digital technologies.
- Studies on the adoption of 4IR technologies by start-up healthcare providers to determine the state of current innovations and future trends in healthcare.

5.5 CONTRIBUTION OF THE STUDY

The research contributes to the body of knowledge on the role of 4IR on healthcare by synthesising 84 research papers on the subject matter. The study identified the main 4IR technologies that are driving the digital transformation, the areas of healthcare being transformed, and the impact of the transformation on quality of medical care, medical costs and quality of life. The results from this SLR can benefit start-up healthcare providers through the in-depth analysis and discussion of the current state of innovations, technological opportunities and challenges to drive new innovations in healthcare delivery.

5.6 CONCLUSION

4IR technologies provide interventions against the main challenges of conventional healthcare systems, including increased costs of medical care, poor quality medical care, and poor quality of life. The increasing rate of chronic illnesses due to an aging population, reduced national health budgets, and lack of universal access to healthcare due to unequal distribution of medical resources, have the biggest impact on medical costs, quality of medical care and quality of life. Digital technologies are transforming healthcare to mitigate against these challenges.

The SLR showed that 4IR technologies are continuously transforming many industries and the healthcare industry is no exception. The most pivotal 4IR technologies in the healthcare sector include IoT, AI, Big data, Cloud computing, and Blockchain. The transformation of healthcare is evolutionary, revolutionary or disruptive as it tracks innovation in ICT industry. The main areas of transformation include personalised care, precision medicine, telemedicine, mobile health, smart/networked healthcare, remote health monitoring, clinical decision support, and digital skills.

Advancements in ICT industry are gradually filtering through to the healthcare industry albeit at a slower pace. First-generation digital technologies transformed healthcare from conventional to digital, and from digital to intelligent. The next-generation 4IR technologies are transforming healthcare from centralised, encounter-based, and reactive to a distributed, continuous, connected and proactive personalised care system.

The uptake of 4IR technologies in the healthcare industry is increasing with more potential opportunities identified and presented for certification in preparation for implementation.

There are a number of challenges hindering the adoption of new technologies in healthcare. These barriers include technical limitations due to legacy ICT systems, poor clinical data quality and lack of interoperability, governance and policy issues including ethical considerations, and lack of trust in technology by both patients and healthcare professionals. However, the opportunities outweigh the challenges. Several factors, including the global Covid-19 pandemic and advancements in ICT are accelerating the adoption of technology at scale in the healthcare industry.

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APPENDIX A: 4IR TECHNOLOGIES DRIVING THE TRANSFORMATION OF HEALTHCARE

4IR technologies driving the transformation of healthcare	
AI	Li, D. (2019); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Lee, D., & Yoon, S. N. (2021); Jin, X., Liu, C., Xu, T., Su, L., & Zhang, X. (2020); Jin, X., Liu, C., Xu, T., Su, L., & Zhang, X. (2020); Noorbakhsh-Sabet, N., Zand, R., Zhang, Y., & Abedi, V. (2019); Orphanidou, C. (2019); Williams, A. M., Liu, Y., Regner, K. R., Jotterand, F., Liu, P., & Liang, M. (2018); McGrow, K. (2019); Hazarika, I. (2020); Wang, L., & Alexander, C. A. (2020); Arora, A. (2020); Cosgriff, C. V., Celi, L. A., & Stone, D. J. (2019); Tobore, I., Li, J., Yuhang, L., Al-Handarish, Y., Kandwal, A., Nie, Z., & Wang, L. (2019); Nasajpour, M., Pouriyeh, S., Parizi, R. M., Dorodchi, M., Valero, M., & Arabnia, H. R. (2020); Germain, M., Caputo, F., Metcalfe, S., Tosi, G., Spring, K., Åslund, A. K. O., . . . Schmid, R. (2020); Ilan, Y. (2021); Wiens, J., & Shenoy, E. S. (2018); Alami, H., Lehoux, P., Denis, J.-L., Motulsky, A., Petitgand, C., Savoldelli, M., . . . Fortin, J.-P. (2021); Kang, M., Park, E., Cho, B. H., & Lee, K.-S. (2018); Alexander, A., McGill, M., Tarasova, A., Ferreira, C., & Zurkiya, D. (2019); Latif, S., Qadir, J., Qayyum, A., Usama, M., & Younis, S. (2021); Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019); Jheng, Y.-C., Kao, C.-L., Yarmishyn, A. A., Chou, Y.-B., Hsu, C.-C., Lin, T.-C., . . . Hwang, D.-K. (2020)
IoT	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Jagadeeswari, V., Subramaniyaswamy, V., Logesh, R., & Vijayakumar, V. (2018); Zheng, X., Sun, S., Mukkamala, R. R., Vatrapu, R., & Ordieres-Meré, J. (2019); Uslu, B. Ç., Okay, E., & Dursun, E. (2020); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Mansour, R. F., Amraoui, A. E., Nouaouri, I., Díaz, V. G., Gupta, D., & Kumar, S. (2021); Celesti, A., Ruggeri, A., Fazio, M., Galletta, A., Villari, M., & Romano, A. (2020); Kukafka, R. (2019); Rubí, J. N. S., & Gondim, P. R. (2019); Pathinarupothi, R. K., Durga, P., & Rangan, E. S. (2019); Dimitrov, D. V. (2016); Roehrs, A., da Costa, C. A., Righi, R. d. R., & de Oliveira, K. S. F. (2017); Hejazi Dehaghani, S. A., Hajrahimi, B., & Dehaghani Hejazi, S. M. (2020); Rathore, M. M., Ahmad, A., Paul, A., Wan, J., & Zhang, D. (2016); Kang, M., Park, E., Cho, B. H., & Lee, K.-S. (2018); Ahad, A., Tahir, M., Aman Sheikh, M., Ahmed, K. I., Mughees, A., & Numani, A. (2020); Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., & Kim, S. W. (2020); Meinert, E., Van Velthoven, M., Brindley, D., Alturkistani, A., Foley, K., Rees, S., . . . de Pennington, N. (2018); Rubí & Gondim, 2019; Kelly, J. T., Campbell, K. L., Gong, E., & Scuffham, P. (2020); Hirose, J., Wakata, Y., Tagi, M., & Tamaki, Y. (2020); Muhammed, T., Mehmood, R., Albeshri, A., & Katib, I. (2018)
Big data	Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Orphanidou, C. (2019); Jagadeeswari, V., Subramaniyaswamy, V., Logesh, R., & Vijayakumar, V. (2018); Cai, Q., Wang, H., Li, Z., & Liu, X. (2019); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Wang, L., & Alexander, C. A. (2020); Cosgriff, C. V., Celi, L. A., & Stone, D. J. (2019); Cosgriff, C. V., Celi, L. A., & Stone, D. J. (2019); Miotto, R., Wang,

4IR technologies driving the transformation of healthcare	
	F., Wang, S., Jiang, X., & Dudley, J. T. (2018); Tobore, I., Li, J., Yuhang, L., Al-Handarish, Y., Kandwal, A., Nie, Z., & Wang, L. (2019); Bublitz, F. M., Oetomo, A., Sahu, S. K., Kuang, A., Fadrique, L. X., Velmovitsky, P. E., . . . Morita, P. P. (2019); Vellido, A., Ribas, V., Morales, C., Ruiz Sanmartín, A., & Ruiz Rodríguez, J. C. (2018); Rathore, M. M., Ahmad, A., Paul, A., Wan, J., & Zhang, D. (2016); Lun, K.-C. (2018)
5G	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Ahad, A., Tahir, M., Aman Sheikh, M., Ahmed, K. I., Mughees, A., & Numani, A. (2020); Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., & Kim, S. W. (2020); Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021); Muhammed, T., Mehmood, R., Albeshri, A., & Katib, I. (2018)
Blockchain	Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Anjum, H. F., Rasid, S. Z. A., Khalid, H., Alam, M. M., Daud, S. M., Abas, H., . . . Yusof, M. F. (2020); Kang, M., Park, E., Cho, B. H., & Lee, K.-S. (2018); Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., & Kim, S. W. (2020)
Cloud computing	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Wang, L., & Alexander, C. A. (2020); Celesti, A., Ruggeri, A., Fazio, M., Galletta, A., Villari, M., & Romano, A. (2020); Kang, M., Park, E., Cho, B. H., & Lee, K.-S. (2018); Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021); Muhammed, T., Mehmood, R., Albeshri, A., & Katib, I. (2018)

APPENDIX B: AREA OF HEALTHCARE TRANSFORMATION

Area of healthcare transformation	
Personalised care and Precision medicine	Li, D. (2019); Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Jagadeeswari, V., Subramaniyaswamy, V., Logesh, R., & Vijayakumar, V. (2018); Williams, A. M., Liu, Y., Regner, K. R., Jotterand, F., Liu, P., & Liang, M. (2018); Wang, L., & Alexander, C. A. (2020); Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018); Goldsack, J. C., & Zanetti, C. A. (2020); Huang, F., Brouqui, P., & Boudjema, S. (2021); Castro, E. M. J., & Faria Araújo, N. M. (2020); Nasajpour, M., Pouriyeh, S., Parizi, R. M., Dorodchi, M., Valero, M., & Arabnia, H. R. (2020); Chute, C., & French, T. (2019); Araiza-Garaygordobil, D., Jordán-Ríos, A., Sierra-Fernández, C., & Juárez-Orozco, L. E. (2020); Erikainen, S., Pickersgill, M., Cunningham-Burley, S., & Chan, S. (2019); Chen, Y., Guzauskas, G. F., Gu, C., Wang, B. C., Furnback, W. E., Xie, G., . . . Garrison, L. P. (2016); Kang, M., Park, E., Cho, B. H., & Lee, K.-S. (2018); Alexander, A., McGill, M., Tarasova, A., Ferreira, C., & Zurkiya, D. (2019)
Telemedicine	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Mansour, R. F., Amraoui, A. E., Nouaouri, I., Díaz, V. G., Gupta, D., & Kumar, S. (2021); Wang, L., & Alexander, C. A. (2020); Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., Merrell, R. C., Macedonia, C., . . . Geiling, J. (2016)
Remote health monitoring	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Orphanidou, C. (2019); Jagadeeswari, V., Subramaniyaswamy, V., Logesh, R., & Vijayakumar, V. (2018); Sartori, F. (2020); Lee, D., & Yoon, S. N. (2021); Avila, K., Sanmartin, P., Jabba, D., & Jimeno, M. (2017); Wang, L., & Alexander, C. A. (2020); Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., Merrell, R. C., Macedonia, C., . . . Geiling, J. (2016); Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018); Tobore, I., Li, J., Yuhang, L., Al-Handarish, Y., Kandwal, A., Nie, Z., & Wang, L. (2019); Islam, M. M., Rahaman, A., & Islam, M. R. (2020); Yang, X., Wang, X., Li, X., Gu, D., Liang, C., Li, K., . . . Zhong, J. (2020); Huang, F., Brouqui, P., & Boudjema, S. (2021); Dimitrov, D. V. (2016); Rathore, M. M., Ahmad, A., Paul, A., Wan, J., & Zhang, D. (2016); Kang, M., Park, E., Cho, B. H., & Lee, K.-S. (2018); Latif, S., Qadir, J., Qayyum, A., Usama, M., & Younis, S. (2021); Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019); Mieronkoski, R., Azimi, I., Rahmani, A. M., Aantaa, R., Terävä, V., Liljeberg, P., & Salanterä, S. (2017); Fischer, G. S., Righi, R. d. R., Costa, C. A. d., Galante, G., & Griebler, D. (2019); Sriram, R. D., & Subrahmanian, E. (2020); Greco, L., Percannella, G., Ritrovato, P., Tortorella, F., & Vento, M. (2020)
Mobile health	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Sartori, F. (2020); Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018); Tobore, I., Li, J., Yuhang, L., Al-Handarish, Y., Kandwal, A., Nie, Z., & Wang, L. (2019); Sadoughi, F., Behmanesh, A., & Sayfouri, N. (2020); Roehrs, A., da Costa, C. A., Righi, R. d. R., & de Oliveira, K. S. F. (2017); Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021)

Area of healthcare transformation	
Smart health and networked healthcare	Ahad, A., Tahir, M., & Yau, K. L. (2019); Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Cai, Q., Wang, H., Li, Z., & Liu, X. (2019); Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., Merrell, R. C., Macedonia, C., . . . Geiling, J. (2016); Yamin, M. (2018); Rubí & Gondim, 2019; Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021)
Resource management	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Uslu, B. Ç., Okay, E., & Dursun, E. (2020); Xu, J., Xue, K., & Zhang, K. (2019); Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., Merrell, R. C., Macedonia, C., . . . Geiling, J. (2016); Javaid, M., & Khan, I. H. (2021); Hejazi Dehaghani, S. A., Hajrahimi, B., & Dehaghani Hejazi, S. M. (2020); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Sriram, R. D., & Subrahmanian, E. (2020)
Data management	Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Cai, Q., Wang, H., Li, Z., & Liu, X. (2019); Yamin, M. (2018); Scott, P., Dunscombe, R., Evans, D., Mukherjee, M., & Wyatt, J. (2018); Wiens, J., & Shenoy, E. S. (2018); Vellido, A., Ribas, V., Morales, C., Ruiz Sanmartín, A., & Ruiz Rodríguez, J. C. (2018); Dimitrov, D. V. (2016); Erikainen, S., Pickersgill, M., Cunningham-Burley, S., & Chan, S. (2019); Mieronkoski, R., Azimi, I., Rahmani, A. M., Aantaa, R., Terävä, V., Liljeberg, P., & Salanterä, S. (2017); Mieronkoski, R., Azimi, I., Rahmani, A. M., Aantaa, R., Terävä, V., Liljeberg, P., & Salanterä, S. (2017); Meinert, E., Van Velthoven, M., Brindley, D., Alturkistani, A., Foley, K., Rees, S., . . . de Pennington, N. (2018); Au-Yong-Oliveira, M., Pesqueira, A., Sousa, M. J., Dal Mas, F., & Soliman, M. (2021); Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021)
Clinical decision support	Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Orphanidou, C. (2019); Uslu, B. Ç., Okay, E., & Dursun, E. (2020); Lee, D., & Yoon, S. N. (2021); Mansour, R. F., Amraoui, A. E., Nouaouri, I., Díaz, V. G., Gupta, D., & Kumar, S. (2021); Williams, A. M., Liu, Y., Regner, K. R., Jotterand, F., Liu, P., & Liang, M. (2018); Galmarini, C. M., & Lucius, M. (2020); Arora, A. (2020); Xu, J., Xue, K., & Zhang, K. (2019); Pathinarupothi, R. K., Durga, P., & Rangan, E. S. (2019); Mansour, R. F., Amraoui, A. E., Nouaouri, I., Díaz, V. G., Gupta, D., & Kumar, S. (2021); Hazarika, I. (2020); Rubí, J. N. S., & Gondim, P. R. (2019); Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019); Fischer, G. S., Righi, R. d. R., Costa, C. A. d., Galante, G., & Griebler, D. (2019)
Remote surgery and telesurgery	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. Li, D. (2019); Lee, D., & Yoon, S. N. (2021); Castro, E. M. J., & Faria Araújo, N. M. (2020); Yamin, M. (2018); Alexander, A., McGill, M., Tarasova, A., Ferreira, C., & Zurkiya, D. (2019); Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., & Kim, S. W. (2020)
Digital skills development	McGrow, K. (2019); Hazarika, I. (2020); Cosgriff, C. V., Celi, L. A., & Stone, D. J. (2019); Xu, J., Xue, K., & Zhang, K. (2019); Goldsack, J. C., & Zanetti, C. A. (2020); K.C. (2018); Au-Yong-Oliveira, M., Pesqueira, A., Sousa, M. J., Dal

Area of healthcare transformation	
	Mas, F., & Soliman, M. (2021)
Covid-19 pandemic	Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Ramallo-González, A. P., González-Vidal, A., & Skarmeta, A. F. (2021); Huang, F., Brouqui, P., & Boudjema, S. (2021); Singh, R. P., Javaid, M., Haleem, A., & Suman, R. (2020); Javaid, M., & Khan, I. H. (2021); Nasajpour, M., Pouriyeh, S., Parizi, R. M., Dorodchi, M., Valero, M., & Arabnia, H. R. (2020); Benis, A., Tamburis, O., Chronaki, C., & Moen, A. (2021); Kelly, J. T., Campbell, K. L., Gong, E., & Scuffham, P. (2020); Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M. (2021)

APPENDIX C: IMPACT OF DIGITAL TRANSFORMATION IN HEALTHCARE

Impact of digital transformation in healthcare	
High quality medical services	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Orphanidou, C. (2019); Uslu, B. Ç., Okay, E., & Dursun, E. (2020); Lee, D., & Yoon, S. N. (2021); Hazarika, I. (2020); Vandenberg, O., Durand, G., Hallin, M., Diefenbach, A., Gant, V., Murray, P., . . . van Belkum, A. (2020); Xu, J., Xue, K., & Zhang, K. (2019); Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., Merrell, R. C., Macedonia, C., . . . Geiling, J. (2016); Nasajpour, M., Pouriyeh, S., Parizi, R. M., Dorodchi, M., Valero, M., & Arabnia, H. R. (2020); Sadoughi, F., Behmanesh, A., & Sayfouri, N. (2020); Araiza-Garaygordobil, D., Jordán-Ríos, A., Sierra-Fernández, C., & Juárez-Orozco, L. E. (2020); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., & Kim, S. W. (2020); Sriram, R. D., & Subrahmanian, E. (2020)
Reduction of medical costs	Li, D. (2019); Ahad, A., Tahir, M., & Yau, K. L. (2019); Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R. B., & Nawaz, M. (2020); Orphanidou, C. (2019); Lee, D., & Yoon, S. N. (2021); McGrow, K. (2019); Wang, L., & Alexander, C. A. (2020); Vandenberg, O., Durand, G., Hallin, M., Diefenbach, A., Gant, V., Murray, P., . . . van Belkum, A. (2020); Xu, J., Xue, K., & Zhang, K. (2019); Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., Merrell, R. C., Macedonia, C., . . . Geiling, J. (2016); Castro, E. M. J., & Faria Araújo, N. M. (2020); Ilan, Y. (2021); Nasajpour, M., Pouriyeh, S., Parizi, R. M., Dorodchi, M., Valero, M., & Arabnia, H. R. (2020); Sadoughi, F., Behmanesh, A., & Sayfouri, N. (2020); Rubí, J. N. S., & Gondim, P. R. (2019); Dimitrov, D. V. (2016); Araiza-Garaygordobil, D., Jordán-Ríos, A., Sierra-Fernández, C., & Juárez-Orozco, L. E. (2020); McNabb, T., Myers, T., Wicking, K., Lei, L., & Xiang, W. (2018); Chen, Y., Guzauskas, G. F., Gu, C., Wang, B. C., Furnback, W. E., Xie, G., . . . Garrison, L. P. (2016); Hejazi Dehaghani, S. A., Hajrahimi, B., & Dehaghani Hejazi, S. M. (2020); Latif, S., Qadir, J., Qayyum, A., Usama, M., & Younis, S. (2021); Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021); Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019); Lun, K.C. (2018); Kelly, J. T., Campbell, K. L., Gong, E., & Scuffham, P. (2020); Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021); Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M. (2021)
Improved quality of life	Dimitrov, D. V. (2016); Kang, M., Park, E., Cho, B. H., & Lee, K.-S. (2018); Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019); Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., & Kim, S. W. (2020); Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021)

APPENDIX D: QUALITY ASSESSMENT SCORES

Author	QA1	QA2	QA3	QA4	Total score
Abd-Alrazaq, A., Alajlani, M., Alhuwail, D., Schneider, et al.	1	1	1	0	3
Abdel-Basset, M., Chang, V., & Nabeeh, N. A.	1	1	1	1	4
Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M.	1	1	1	1	4
Ahad, A., Tahir, M., & Yau, K. L.	1	1	1	1	4
Ahad, A., Tahir, M., Aman Sheikh, M., Ahmed, K. I., Mughees, A., & Numani, A.	1	1	1	1	4
Akhbarifar, S., Javadi, H. H., Rahmani, A. M., & Hosseinzadeh, M.	1	0	1	1	3
Alami, H., Lehoux, P., Auclair, Y., de Guise, M., et al.	1	1	1	1	4
Alami, H., Lehoux, P., Denis, J. L., Motulsky, A., et al.	1	1	1	1	4
Alemayehu, D., & Berger, M. L.	1	1	1	0	3
Alexander, A., McGill, M., Tarasova, A., Ferreira, C., et al.	1	1	1	1	4
Ali, M. S., Vecchio, M., Putra, G. D., Kanhere, S. S., et al.	1	1	1	0	3
Almeida, J. P.	1	0	1	1	3
AlMuhaideb, S., Alswailem, O., Alsubaie, N., Ferwana, I., et al.	1	0	1	0	2
Andreas, A., Mavromoustakis, C. X., Mastorakis, G., Do, D.T., et al.	1	0	1	0	2
Anjum, H. F., Rasid, S. Z. A., Khalid, H., Alam, M. M., et al.	1	1	1	1	4
Araiza-Garaygordobil, D., Jordán-Ríos, A., Sierra-Fernández, C., & Juárez-Orozco, L. E.	1	1	1	1	4
Armgarth, A., Pantzare, S., Arven, P., Lassnig, R., et al.	1	1	1	1	4
Arora, A.	1	1	1	1	4
Asan, O., Bayrak, A. E., & Choudhury, A.	1	1	1	1	4
Ashrafian, H., & Darzi, A.	0	0	1	0	1
Au, R., Ritchie, M., Hardy, S., Ang, T. F., et al.	1	0	1	1	3
Auffray, C., Balling, R., Barroso, I., Bencze, L., et al.	1	1	1	1	4
Au-Yong-Oliveira, M., Pesqueira, A., Sousa, M. J., Dal Mas, F., et al.	1	1	1	1	4
Avila, K., Sanmartin, P., Jabba, D., & Jimeno, M.	1	1	1	1	4
Ayoola, I., Wetzels, M., Peters, P., van Berlo, S., et al.	1	0	1	1	3
Bayo-Monton, J.-L., Martinez-Millana, A., Han, W., Fernandez-Llatas, C., et al.	1	1	1	1	4
Bayram, M., Springer, S., Garvey, C. K., & Özdemir, V.	1	0	1	1	3
Benis, A., Tamburis, O., Chronaki, C., & Moen, A.	1	1	1	1	4
Bhattad, P. B., & Jain, V.	1	1	1	1	4
Bublitz, F. M., Oetomo, A., Sahu, K. S., Kuang, A., et al.	1	1	1	1	4
Buchanan, C., Howitt, M. L., Wilson, R., Booth, R. G., et al.	1	1	1	1	4
Cai, Q., Wang, H., Li, Z., & Liu, X.	1	1	1	1	4
Castro, E. M., & Faria Araújo, N. M.	1	1	1	1	4
Celesti, A., Ruggeri, A., Fazio, M., Galletta, A., et al.	1	1	1	1	4
Chen, Y., Guzauskas, G. F., Gu, C., Wang, B. C., et al.	1	1	1	1	4

Author	QA1	QA2	QA3	QA4	Total score
Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., et al.	1	1	1	1	4
Chute, C., & French, T.	1	1	1	1	4
Coiera, E.	0	1	1	1	3
Cosgriff, C. V., Celi, L. A., & Stone, D. J.	1	1	1	1	4
Coulby, G., Clear, A., Jones, O., Young, F., et al.	1	1	1	1	4
Cresswell, K., Cunningham-Burley, S., & Sheikh, A.	1	0	1	1	3
Dash, S. P.	1	1	1	0	3
Devine, B.	0	1	1	1	3
Dimitrov, D. V.	1	1	1	1	4
Drozdowicz, M., Ganzha, M., & Paprzycki, M.	1	1	0	1	3
Dwivedi, A. D., Srivastava, G., Dhar, S., & Singh, R.	1	1	1	0	3
Echelard, J. F., Méthot, F., Nguyen, H. A., & Pomey, M. P.	1	1	0	1	3
Ekeland, A. G., & Linstad, L. H.	1	0	1	1	3
Elagan, S. K., Abdelwahab, S. F., Zanaty, E. A., Alkinani, M. H., et al.	1	0	1	1	3
Elhoseny, M., Ramírez-González, G., Abu-Elnasr, O. M., Shawkat, S. A., et al.	1	1	0	1	3
Erikainen, S., Pickersgill, M., Cunningham-Burley, S., & Chan, S.	1	1	1	1	4
Fischer, G. S., Righi, R. d. R., Costa, C. A. d., Galante, G., et al.	1	1	1	1	4
Fogel, A. L., & Kvedar, J. C.	1	0	1	1	3
Galmarini, C. M., & Lucius, M.	1	1	1	1	4
Gardašević, G., Katzis, K., Bajić, D., & Berbakov, L.	1	0	1	1	3
Germain, M., Caputo, F., Metcalfe, S., Tosi, G., et al.	1	1	1	1	4
Giordanengo, A.	1	1	0	0	2
Goldsack, J. C., & Zanetti, C. A.	1	1	1	1	4
Gopal, G., Suter-Crazzolara, C., Toldo, L., & Eberhardt, W.	0	0	1	1	2
Greco, L., Percannella, G., Ritrovato, P., Tortorella, F., et al.	1	1	1	1	4
Gunasekeran, D. V., Tseng, R., Tham, Y. C., & Wong, T. Y.	1	0	1	1	3
Habibzadeh, H., Dinesh, K., Shishvan, O. R., Boggio-Dandry, A., et al.	1	0	1	1	3
Hadi, M. S., Lawey, A. Q., El-Gorashi, T. E., & Elmirghani, J. M. H.	1	0	1	1	3
Hameed, K., Bajwa, I. S., Sarwar, N., Anwar, W., et al.	1	1	1	1	4
Hazarika, I.	1	1	1	1	4
Hejazi Dehaghani, S. A., Hajrahimi, B., & Dehaghani Hejazi, S. M.	1	1	1	1	4
Hirose, J., Wakata, Y., Tagi, M., & Tamaki, Y.	1	1	1	1	4
Horgan, D., Bernini, C., Thomas, P. P., & Morre, S. A.	1	0	1	1	3
Horgan, D., Romao, M., Morré, S. A., & Kalra, D.	1	0	1	1	3
Huang, F., Brouqui, P., & Boudjema, S.	1	1	1	1	4
Ibrahim, S. A., Charlson, M. E., & Neill, D. B.	1	0	1	1	3
Ilan, Y.	1	1	1	1	4
Ishii, E., Ebner, D. K., Kimura, S., Agha-Mir-Salim, L., et al.	1	0	1	1	3

Author	QA1	QA2	QA3	QA4	Total score
Islam, M. M., Rahaman, A., & Islam, M. R.	1	1	1	1	4
Ismail, L., Materwala, H., Karduck, A. P., & Adem, A.	1	1	0	1	3
Jagadeeswari, V., Subramaniyaswamy, V., Logesh, R., & Vijayakumar, V.	1	1	1	1	4
Jamil, F., Ahmad, S., Iqbal, N., & Kim, D.H.	1	1	1	0	3
Javaid, M., & Khan, I. H.	1	1	1	1	4
Jheng, Y. C., Kao, C. L., Yarmishyn, A. A., Chou, Y.-B., et al.	1	1	1	1	4
Jin, X., Liu, C., Xu, T., Su, L., et al.	1	1	1	1	4
Kang, M., Park, E., Cho, B. H., & Lee, K.-S.	1	1	1	1	4
Kelly, J. T., Campbell, K. L., Gong, E., & Scuffham, P.	1	1	1	1	4
Kim, H. K., & Lee, C. W.	1	0	0	1	2
Kim, J., Kam, H. J., Park, Y. R., Yoo, S., et al.	1	0	1	1	3
Kong, X., Ai, B., Kong, Y., Su, L., et al.	1	0	1	1	3
Konstantinidis, S. T., Billis, A., Wharrad, H., & Bamidis, P. D.	1	1	1	0	3
Kricka, L. J.	1	0	1	1	3
Kristoffersson, A., & Lindén, M.	1	0	1	0	2
Kukafka, R.	1	1	1	1	4
Kyriazis, D., Autexier, S., Boniface, M., Engen, V., et al.	1	1	1	1	4
Latif, S., Qadir, J., Qayyum, A., Usama, M., et al.	1	1	1	1	4
Lee, D., & Yoon, S. N.	1	1	1	1	4
Lehne, M., Sass, J., Essenwanger, A., Schepers, J., et al.	1	1	0	0	2
Lewis, S. J., Gandomkar, Z., & Brennan, P. C.	1	1	0	1	3
Li, D.	1	1	1	1	4
Li, Y., Rao, S., Solares, J. R., Hassaine, A., et al.	1	0	1	1	3
Lin, S. Y., Mahoney, M. R., & Sinsky, C. A.	1	1	1	1	4
Lo, B. P., Ip, H., & Yang, G. Z.	1	1	1	1	4
Lopez-Barbosa, N., Gamarra, J. D., & Osma, J. F.	1	0	1	1	3
Lun, K.-C.	1	1	1	1	4
Lysaght, T., Lim, H. Y., Xafis, V., & Ngiam, K. Y.	1	0	1	1	3
Machluf, Y., Tal, O., Navon, A., & Chaiter, Y.	1	0	0	0	1
Madanian, S., & Parry, D.	1	1	0	1	3
Madanian, S., Parry, D. T., Airehrour, D., & Cherrington, M.	1	1	1	1	4
Mamoshina, P., Ojomoko, L., Yanovich, Y., Ostrovski, A., et al.	1	0	0	1	2
Mansour, R. F., Amraoui, A. E., Nouaouri, I., Díaz, V. G., et al.	1	1	1	1	4
Mattei, P.	1	0	1	1	3
Mavrogiorgou, A., Kiourtis, A., Perakis, K., Miltiadou, D., et al.	1	1	0	1	3
Mavrogiorgou, A., Kiourtis, A., Perakis, K., Pitsios, S., et al.	1	1	0	1	3
McGrow, K.	1	1	1	1	4
McNabb, T., Myers, T., Wicking, K., Lei, L., et al.	1	1	1	1	4
Mehta, N., Pandit, A., & Shukla, S.	1	0	1	1	3
Meinert, E., Van Velthoven, M., Brindley, D., Alturkistani, A., et al.	1	1	1	1	4
Meskó, B., Hetényi, G., & Győrffy, Z.	1	1	1	1	4

Author	QA1	QA2	QA3	QA4	Total score
Mieronkoski, R., Azimi, I., Rahmani, A. M., Aantaa, R., et al.	1	1	1	1	4
Miotto, R., Wang, F., Wang, S., Jiang, X., et al.	1	1	1	1	4
Mohamed Shakeel, P., Baskar, S., Sarma Dhulipala, V. R., Mishra, S., et al.	1	1	0	1	3
Muhammed, T., Mehmood, R., Albeshri, A., & Katib, I.	1	1	1	1	4
Murphy, K., Di Ruggiero, E., Upshur, R., Willison, D. J., et al.	1	1	1	1	4
Naqa, I. E., Kosorok, M. R., Jin, J., Mierzwa, M., et al.	1	0	1	1	3
Nasajpour, M., Pouriyeh, S., Parizi, R. M., Dorodchi, M., et al.	1	1	1	1	4
Nazir, S., Khan, S., Khan, H. U., Ali, S., et al.	1	1	1	1	4
Nebeker, C., Torous, J., & Bartlett Ellis, R. J.	1	0	1	0	3
Nelson, C. A., Butte, A. J., & Baranzini, S. E.	1	0	1	1	3
Noorbakhsh-Sabet, N., Zand, R., Zhang, Y., & Abedi, V.	1	1	1	1	4
Oren, O., Gersh, B. J., & Bhatt, D. L.	1	1	0	0	2
Orphanidou, C.	1	1	1	1	4
O'Sullivan, A., Henrick, B., Dixon, B., Barile, D., et al.	1	0	1	1	3
Park, A., Chang, H., & Lee, K. J.	1	1	1	1	4
Pathinarupothi, R. K., Durga, P., & Rangan, E. S.	1	1	1	1	4
Pool, J., Fatehi, F., Hassandoust, F., & Akhlaghpour, S.	1	0	0	1	2
Prosperi, M., Min, J. S., Bian, J., & Modave, F.	1	1	1	1	4
Qadir, J., Mujeeb-U-Rahman, M., Rehmani, M. H., Pathan, A. K., et al.	0	0	1	1	2
Qadri, Y. A., Nauman, A., Zikria, Y. B., Vasilakos, A. V., et al.	1	1	1	1	4
Qoronfleh, M. W., Chouchane, L., Mifsud, B., Al Emadi, M., et al.	1	0	1	1	3
Qu, Y., Ming, X., Qiu, S., Zheng, M., et al.	1	0	0	0	1
Rahman, M. S., Peeri, N. C., Shrestha, N., Zaki, R., et al.	1	1	1	1	4
Ramallo-González, A. P., González-Vidal, A., & Skarmeta, A. F.	1	1	1	1	4
Ranchal, R., Bastide, P., Wang, X., Gkoulalas-Divanis, A., et al.	1	0	1	1	3
Rathore, M. M., Ahmad, A., Paul, A., Wan, J., et al.	1	1	1	1	4
Raza, S., & Luheshi, L.	1	0	1	1	3
Reddy, V., & Brumpton, L.	0	0	0	1	1
Reza Soroushmehr, S. M., & Najarian, K.	1	1	1	0	3
Roehrs, A., da Costa, C. A., Righi, R. d. R., & de Oliveira, K. S. F.	1	1	1	1	4
Rosen, J. M., Kun, L., Mosher, R. E., Grigg, E., et al.	1	1	1	1	4
Rubí, J. N., & L Gondim, P. R.	1	1	1	1	4
Sadoughi, F., Behmanesh, A., & Sayfouri, N.	1	1	1	1	4
Said, A. M., Yahyaoui, A., & Abdellatif, T.	1	0	1	1	3
Sarfraz, Z., Sarfraz, A., Iftikar, H. M., & Akhund, R.	1	0	1	1	3
Sartori, F.	1	1	1	1	4
Satamraju, K. P., & Malarkodi, B.	1	1	0	1	3
Scott, P., Dunscombe, R., Evans, D., Mukherjee, M., et al.	1	1	1	1	4
Seh, A. H., Zarour, M., Alenezi, M., Sarkar, A. K., et al.	1	0	0	1	2
Seyhan, A. A., & Carini, C.	1	0	1	1	3
Shah, P., Kendall, F., Khozin, S., Goosen, R., et al.	1	0	0	1	2

Author	QA1	QA2	QA3	QA4	Total score
Shamayleh, A., Awad, M., & Farhat, J.	1	0	0	1	2
Shaughnessy, A. F., Slawson, D. C., & Duggan, A. P.	0	0	1	1	2
Sheth, A., Jaimini, U., & Yip, H. Y.	1	1	1	1	4
Singh, R. P., Javaid, M., Haleem, A., & Suman, R.	1	1	1	1	4
Sorace, J.	1	0	1	1	3
Sriram, R. D., & Subrahmanian, E.	1	1	1	1	4
Subahi, A. F.	1	0	1	1	3
Sun, Y., Lo, F. P., & Lo, B.	1	1	0	1	3
Thompson, M. E., & Dulin, M. F.	1	1	1	1	4
Tobore, I., Li, J., Yuhang, L., Al-Handarish, Y., et al.	1	1	1	1	4
Tripathi, G., Ahad, M. A., & Paiva, S.	1	1	0	1	3
Uslu, B. Ç., Okay, E., & Dursun, E.	1	1	1	1	4
Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A.	1	0	1	1	3
Vandenberg, O., Durand, G., Hallin, M., Diefenbach, A., et al.	1	1	1	1	4
Vellido, A., Ribas, V., Morales, C., Ruiz Sanmartín, A., et al.	1	1	1	1	4
Velupillai, S., Suominen, H., Liakata, M., Roberts, A., et al.	1	0	1	0	3
Verdejo Espinosa, Á., Lopez Ruiz, J., Mata Mata, F., & Estevez, M. E.	1	0	1	1	3
Wahl, B., Cossy-Gantner, A., Germann, S., & Schwalbe, N. R.	1	1	1	1	4
Waldman, S. A., & Terzic, A.	1	1	1	0	3
Wang, L., & Alexander, C. A.	1	1	1	1	4
Werner, R., Henningsen, M., Schmitz, R., Guse, A. H., et al.	1	0	0	1	2
Wiens, J., & Shenoy, E. S.	1	1	1	1	4
Williams, A. M., Liu, Y., Regner, K. R., Jotterand, F., et al.	1	1	1	1	4
Wiweko, B., & Zakirah, S. C.	1	0	1	1	3
Wu, J., Tian, X., & Tan, Y.	1	0	1	1	3
Xie, R., Khalil, I., Badsha, S., & Atiquzzaman, M.	1	1	1	0	3
Xu, J., Xue, K., & Zhang, K.	1	1	1	1	4
Yamin, M.	1	1	1	1	4
Yang, X., Wang, X., Li, X., Gu, D., et al.	1	1	1	1	4
Yin, X. C., Liu, Z. G., Ndibanje, B., Nkenyereye, L., et al.	1	1	1	0	3
Yu, S., Ma, Y., Gronsbell, J., Cai, T., et al.	1	0	1	1	3
Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M.	1	1	1	1	4
Zhang, K., & Ling, W.	1	0	1	1	3
Zhang, Z., Brazil, J., Ozkaynak, M., & Desanto, K.	1	0	1	1	3
Zheng, X., Sun, S., Mukkamala, R. R., Vatrapu, R., et al.	1	1	1	1	4