AIoT in Healthcare

A Cooperative Blueprint in China and India

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Foreword

As civilization progresses and advances are made in the study of ecosystems, humans are becoming more concerned about their health and well-being. Medical systems are facing dire challenges. Taking the long view, the world population is aging remarkably, and age-dependent chronic diseases are projected to increase, which will put mounting pressure on the entire medical system. In the short term, medical systems are faced with the ultimate challenge as the COVID-19 pandemic rages across the world, demanding fast reaction and precise forecasts. In order to respond aptly to these issues, healthcare services urgently need transformation via innovative technologies to improve people's lives.

As machine/deep learning, sensors, 5G, and other digital technologies advance, Artificial Intelligence and the Internet of Things (i.e. AIoT) have entered an unprecedented stage of rapid development and are now touching all aspects of the health ecosystem. By enhancing clinical diagnosis performance, rethinking the roles of medical devices, and expanding the capacity of the medical system, AIoT is reshaping the healthcare sector and has catalyzed a consolidation of industrialization in healthcare.

This white paper surveys AIoT in healthcare from a cooperative blueprint in China and India. It starts with a review on the development of the cutting-edge AIoT technologies in healthcare, followed by a closer look at four key areas of AIoT in healthcare, i.e. Smart Data Collection, Proactive Monitorial Systems, Personal Digital Twin systems, and Medical Resource Planning strategies, then presents successful application cases of AIoT for healthcare in China, India, and other regions in the world. Furthermore, this white paper identifies some challenges that lie ahead and reviews research on the issue from both academia and industry. Finally, this white paper offers an outlook on possible developments for AIoT in healthcare going forward.

The BRICS countries, including China and India, are working together to promote technological breakthroughs and innovations of AIoT in healthcare. We hope that publication of this white paper will provide the readers with a deeper understanding of the practical investigations on AIoT from the BRICS countries in this field, thus contributing to the new momentum for development and international cooperation in the global healthcare industry, and promote the construction of a healthcare community for humanity.

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Introduction

The health and well-being of populations are of particular concern with regard to the advancement of civilization and the ecosystem. Humankind is always searching for a path to a better life of health and wellbeing.

Like other technologies, the development of healthcare heavily depends on human data technologies. Progress has not been linear: There were some big steps forward, some steps back, sometimes the field was at a standstill. In ancient times, health used to be completely beyond human understanding. Like many things in the ancient world, health was considered something under God's control and was addressed by holding primitive religious ceremonies where people would pray for physical health and seek spiritual comfort.

It took a slow and difficult process of accumulating experience and knowledge over hundreds of thousands of years before people gained some systematic understanding of the healing power of plants, and began using herbs to treat diseases, prolong life, and maintain health. Deliberately or accidentally, religion promoted herbal-based medicine for healthcare, and the development of healthcare from religion and herbal medicine represents the origin of data collection, which in ancient times was very risky and lacking any practical data analyst or actual understanding of the human body.

In post-industrial civilizations, when physics, chemistry, and biology developed dramatically, more powerful tools spurred the evolution of healthcare. The pharmaceutical field was developed to synthesize drugs, and identify their structural relationships and the natural laws governing their interaction with body cells and biological macromolecules. In particular, after the development of anesthetics, surgery became widely available. With help from other scientific fields, and more importantly, with modern statistics and scientific methodologies, the boosted knowledge of both medicines and the human body stimulated the formation of modern healthcare.

Like many other sciences, modern healthcare developed rapidly until all the “easy” problems were solved. With the current developments in healthcare, traditional data collection and analysis were no longer sufficient. In front of our very eyes, a new horizon forms. Emerging biological pharmaceuticals, nanotechnology, and more importantly, the development of Artificial Intelligence and the Internet of Things (i.e., AIoT) is taking over the frontier of healthcare development. The next era for healthcare will be data- and intelligence-oriented, as shown in the following aspects: (1) To provide better data mining power. For example, gene sequencing needs to analyze 30GB of data for every person. Huge and highly complex protein molecules are challenging human data acquisition and process capability. AIoT provides a natural tool for processing and efficiently analyzing data. (2) To integrate investigations and bring efficiency. For instance, the average cost of drugs for clinical trials is $2.6 billion, of which only 10% can be successfully launched on the market. Ever-increasing development costs pose a grave challenge to drug development. For this reason, it has become a trend to use AIoT technologies to improve efficiency and accuracy. (3) To merge technology seamlessly with human experts and extend human capability. For instance, with the promotion and growth of robot-assisted surgery, minimally invasive surgery plays an important role in general surgery due to its extreme precision, quick recovery time, and reduced pain, which is benefiting more and more patients. (4) To assist the existing system on easy and repeated jobs, and expand the capacity of the medical system. For example, millions of patients are admitted to hospitals each year, each with different diseases, insurance coverage, and services required. Patients often complain due to a lack of customer service and a chaotic medical environment. AIoT can improve patient services, simplify the patient process and better manage patient flow.

In recent years, data acquisition and processing have faced critical challenges. A much larger data volume is collected each day. Due to declining fertility rates and longevity, the world population is aging remarkably. The number of people aged 65 or above is projected to grow from nearly 524 million in 2010 to an estimated 1.5 billion in 2050. Along with the aging of the population, there are increasing healthcare demands. As life expectancy increases, age-dependent chronic diseases such as heart disease, high blood pressure, and diabetes are projected to increase and many causes of those diseases are the results of lifestyle and diet. Finally, the COVID-19 pandemic with rapidly changing conditions across the world brought the ultimate challenge to the medical system, demanding extremely high-volume processing, fast reaction, and precise forecasts. As such, responding to the above issues of the aging population, chronic diseases, and the emergence of public health, healthcare services are in urgent need of being transformed via innovative technologies such as AIoT to improve the quality of life for humankind. For instance, from the perspective of patients, AIoT enables patients to monitor their health conditions or manage many aspects of their lives remotely via wearable monitoring devices, shifting the focus to prevention instead of curing; from the perspective of medical resources, AIoT also facilitates optimal resource allocation, thus ensuring efficient use of every health resource.

This whitepaper reviews the development of cutting-edge AIoT technologies in healthcare, identifies challenges that lie ahead, and imagines how AIoT in the healthcare of tomorrow might develop. Specifically, this survey starts with the background of AIoT in healthcare by covering the foundations of AIoT technologies, including AI and IoT, discussing the role of AIoT in healthcare, and reviewing its development. Then, this white paper takes a closer look at four key areas of cost-effective and reliable health services using AIoT. They are: (1) Smart Data Collection, which uses the IoT technologies for effective collection and analysis of data in health; (2) Proactive Monitorial Systems, where AI technologies are employed for early detection, disease diagnosis, and patient monitoring; (3) Personal Digital Twin systems, customized as a patient replica or virtual care; (4) Medical Resource Scheduling strategies, which use reinforcement learning technologies for effective medical resource matching and optimization. Besides, this white paper presents successful application cases of AIoT for healthcare in China, India, and the other regions in the world with brief analyses for each region. Furthermore, this survey points out challenges in adopting AIoT in healthcare and reviews the research on these challenges from both academia and industry. Challenges that lie ahead include: challenges in trustworthy AI (e.g., data privacy, model transparency, fairness, and autonomy) and technologies (e.g., multi-source heterogeneous data, model capacity, edge computing, model transferability). Lastly, this report describes a vision AIoT in healthcare and future possibilities. It identifies two possible directions of AIoT in healthcare, namely, a privacy-preserving healthcare platform and an intelligent integrated medical service based on big data, and promotes international medical cooperation among BRICs countries and a BRICs health community.

The remainder of this white paper is organized as follows: Section 2 covers the background of AIoT in healthcare. Section 3 takes a closer look at four key areas of AIoT technologies in healthcare. Section 4 describes practical applications of AIoT in healthcare. Section 5 is devoted to the challenges of adopting AIoT in healthcare and research from both academia and industry. Finally, Section 6 concludes with the vision and future possibilities of AIoT in healthcare.

Background of AIoT in healthcare

2.1 Foundations of AIoT

2.1.1 Understanding AI

Artificial Intelligence (AI) is the intelligence demonstrated by machines. The term was first coined by John McCarthy in 1995. Kaplan and Haenlein define AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". In summary, AI aims to study the fundamental theories, methods, and techniques of how to apply machines, especially computer systems, to simulate certain human behaviors. According to a recent market report [1], the global AI market size is expected to be $93.53 billion in 2021 and the compound annual growth rate (CAGR) is expected to be 40.2% from 2021 to 2028.

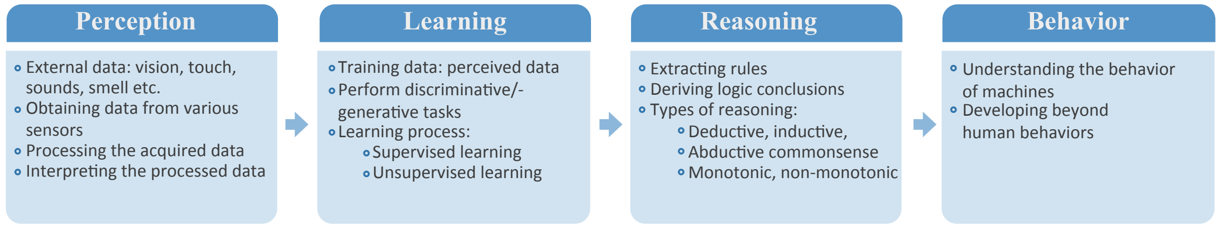

Figure 1 Understanding AI

The main goals of AI are perception acquisition, knowledge learning, decision making, and problem-solving. In general, we hope that AI can perform Perception, Learning, Reasoning, and Behavior as well as or even better than humans. Figure 1 shows the pipeline.

Perception is the bridge between an intelligence system and the real world. Just like humans observe the world around us, perception in AI is the process of obtaining, filtering, and interpreting external data, such as vision[2], touch[3], sounds[4], and smell[5]. Perception in AI systems begins with obtaining the data from various sensors. Then, the acquired data are processed and selected to extract useful information about the surrounding environment or objects. Perception is a fundamental building block of AI systems. Improving the perceptual capabilities of AI systems has always been a key area in AI studies and applications.

Learning contributes to evolving an intelligence system that can perform tasks without being explicitly programmed to do so. Learning algorithms are usually trained on the perceived data and aim to perform discriminative/generative tasks on unseen data or under different environments. The learning process of AI can be roughly divided into two categories: supervised learning and unsupervised learning. Supervised learning adopts both samples and corresponding labels for training, while unsupervised learning only uses collected samples to learn the mode of data.

Reasoning is the process of extracting rules and deriving logical conclusions from existing knowledge and information. For an ideal AI system, the capability of reasoning makes machines think rationally and thus solve complex tasks. In general, reasoning can be divided into several types: deductive reasoning, inductive reasoning, abductive reasoning, commonsense reasoning, monotonic reasoning, and non-monotonic reasoning. All these types will drive new knowledge based on previous observation and knowledge, which allows machines to think like humans.

Behavior is where the study of AI goes beyond computer science and intersects with biology and the social sciences[6]. Humans need to understand the behavior of machines, as doing so may lead to a better understanding of nature and development of behaviors that surpass those of humans.

2.1.2 Understanding IoT

The Internet of Things (IoT), a term coined by Kevin Ashton[7], refers to a global network that realizes the ubiquitous connection between things and people by integrating various sensors, computers, and communication equipment. IoT has been developed rapidly over the last twenty years[8] and has benefited from advances in networking technologies, including Radio Frequency Identification (RFID), Micro Electro Mechanical Systems (MEMS), Machine-to-Machine/Man systems, and Cloud Computing. The techniques of IoT can be applied in many fields, e.g., medicine[9], healthcare[10], agriculture [11], and engineering[12]. According to McKinsey's report[13], the IoT sector will contribute $2.7 to $6.2 trillion to the global economy by 2025.

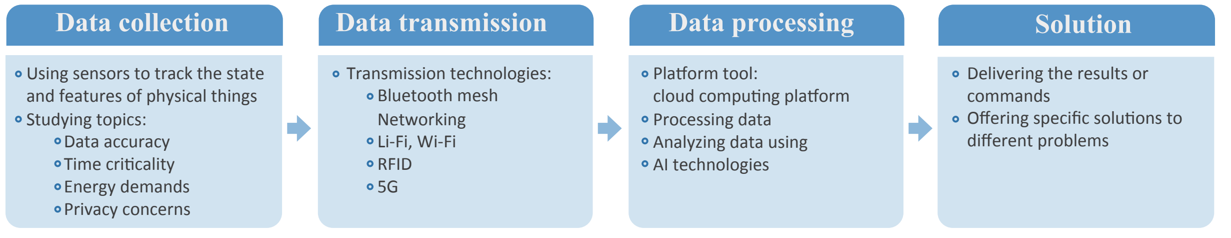

Figure 2 Understanding IoT

A typical IoT architecture has four layers: the data collection layer, the network layer, the platform layer, and the application layer. Based on this partition, we divide the process of IoT into Data collection, Data transmission, Data processing, and Solution. Figure 2 depicts the division.
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Data collection is implemented at the bottom of the IoT architecture. It refers to the process of using sensors to track the state and features of physical things. There is research on many topics[14] related to data collection, such as data accuracy, time criticality, energy demands, and privacy concerns.
Data transmission is implemented in the network layer that lies at the center of the IoT architecture. It consists of multiple transmission technologies, which includes, but is not limited to, Bluetooth mesh networking, Li-Fi, Wi-Fi, RFID, and fifth-generation mobile networks (5G).

Data processing is implemented in the platform layer and aims to process and analyze data from the network layer. In general, data processing-related applications are powered by cloud computing platforms.

Solution is implemented in the application layer, which delivers the results or commands to end devices and offers specific solutions to different problems.

2.1.3 AIoT: Artificial Intelligence of Things

In real-world applications, IoT provides data, computing resources, and application scenarios that could potentially empower large-scale AI applications. With the popularity of IoT devices, a rich set of data can be fed to AI systems, which is the reason why AI has become extremely useful.

Meanwhile, AI plays a growing role in IoT applications and development. In recent years, the emergence of AI technologies has empowered the IoT to be smart, intelligent, safe, and faster. These AI technologies, e.g., machine learning and deep learning, bring the ability to automatically analyze data and identify patterns for IoT. For example, applying AI to the camera device enables auto-detection in cameras; applying AI to incoming sensor telemetry data enables IoT systems to perform real-time analysis. The application of AI makes IoT systems more proactive. Compared to IoT systems that are designed to react to events, Artificial Intelligence of Things (AIoT) systems proactively detect failures and events.

In the future, AIoT will be utilized for industrial automation in a variety of applications including smart cities[15], healthcare[16], manufacturing[17], and agriculture[18]. According to the report[19], the global AIoT market will reach $78.3 Billion by 2026, growing at 39.1% CAGR, and the AI-based device market will be the fastest-growing segment within the AIoT.

2.2 Why is AIoT needed in healthcare?

2.2.1 Healthcare pre-AIoT era and its challenges

The healthcare sector is one of the largest and fastest-growing industries[20]. Healthcare providers, including doctors, nurses, medical administrators, government agencies, pharmaceuticals, equipment manufacturers, and medical insurance companies, treat patients with curative, preventive, rehabilitative, and palliative care. Although investments in healthcare have continued to increase in past decades, related challenges are also constantly emerging. For example, a large number of serious diagnostic errors, mistakes in treatment, an enormous waste of resources, inefficient workflows, inequities, and inadequate time for clinicians with patients[21] all represent hurdles the healthcare system must overcome. In addition to these long-standing issues, novel challenges have emerged with the aging population, increasing demands for care, and limited human capital.

Data-related difficulty. Healthcare data collected from different environments inherently contain various types of bias and noise. For example, medical images from different hospitals are collected using various brand/instrument imaging systems. Low-quality images will further cause difficulties for human interpreters to annotate. Meanwhile, images following different distributions often result in failed generalization of diagnostic decision support systems[27]. In recent years, the increasing adoption of electronic health record systems has expedited the collection of large-scale clinical data. However, medical data that has been collected in massive quantities has exceeded the limits for analysis by clinicians, and the acquisition of large-scale annotated image datasets is prohibitively expensive[29]. Overall, the healthcare sector in the pre-AIoT era was facing challenges related to poor data quality and high data pre-processing cost.

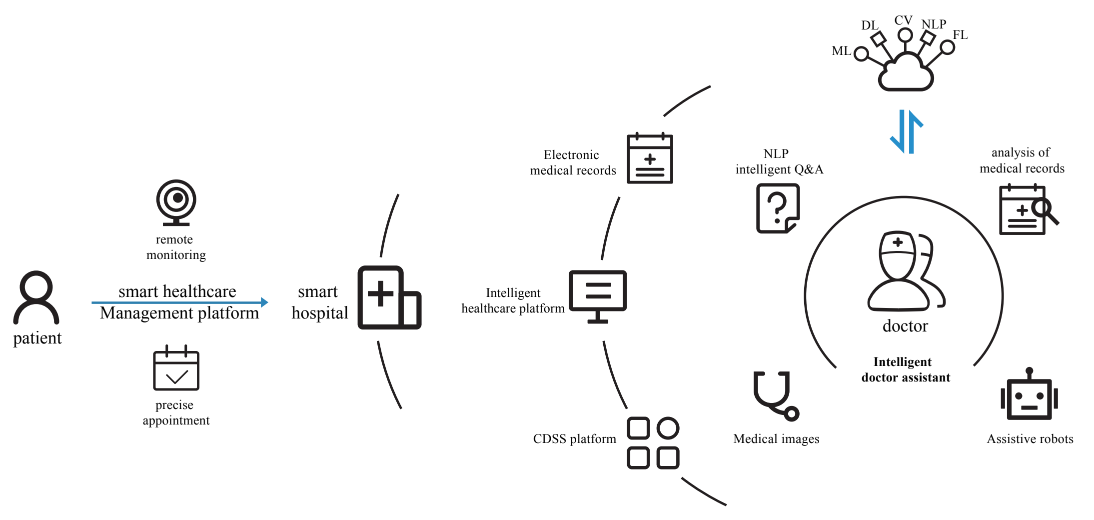
Diagnose / treatment delay. Rapid diagnosis and treatment of acute illnesses are critical to achieving positive outcomes. For example, prioritizing critical cases in radiologists' workflow helps reduce time to treatment and improve diagnostic accuracy [22]. However, it is challenging to diagnose different illnesses in time and ensure that patients are getting accurate treatment. Furthermore, such delays in healthcare results in considerable waste. Nowadays, although in some hospitals many devices are equipped with technologies for continuous health monitoring, the monitoring of a person's health has rarely produced actionable biometric data for healthcare providers[23].

Scarce healthcare resources & Inequalities. Healthcare has long been a limited resource for which there has been an unlimited demand. However, healthcare service costs a great deal. Thus, affordability is one of the most important challenges influencing people's ability to access healthcare. Aging of the population will result in increased healthcare demands and costs[33]. An aging population is more likely to develop chronic conditions with multiple morbidities and puts more pressure on already inadequate health services. Furthermore, not all people have access to healthcare services; thus inequities are one of the most important problems in healthcare [32]. Due to the lack of inclusion of minorities in datasets, many algorithms are embedded with pre-existing inequities. This could widen the present gap in health outcomes.

Inefficient clinical workflow. Storing, accessing, and sharing heterogeneous medical data are complicated. Such a data management infrastructure requires an interoperable application that meets the standard for the representation of clinical information [25]. Currently, data integration across healthcare applications and locations remains spotty and relatively slow. At the same time, assuring privacy and security of data is a critical issue. There exist risks that the details of patient medical history could be leaked, and an individual's identity could be illegally determined by facial recognition or genomic sequence. In addition, tampering with medical data, such as blurring of truth, could be highly detrimental for health [24].

2.2.2 The role of AIoT in healthcare

By enhancing clinical diagnosis performance and redefining the roles of devices in healthcare settings, AI and IoT are together reshaping the healthcare sector [26-27]. AIoT has applications in healthcare that benefit patients, families, physicians, hospitals, industry, and insurance companies. Figure 3 presents some practice scenarios of the adoption of AIoT in healthcare. With the advanced technologies from AIoT, the above problems will likely be effectively solved.



Source: Essence Security

Figure 3 Practice scenarios of the adoption of AIoT in healthcare.

IoT makes remote monitoring possible and empowers physicians to keep track of patients' health more effectively. The connected medical devices will be ubiquitous in all settings, from hospitals to homes, providing a rich variety of health data and guidance through the health portal [26]. IoT also has a major impact on reducing healthcare costs and improving treatment outcomes[31]. IoT has changed people's lives, especially elderly patients, by enabling continuous tracking of health conditions and sending alerts to family members on any disturbance of routine activities[30]. Through risk-tailored longitudinal monitoring provided by IoT, prevention and early detection of disease is possible[23].

AI is transforming every aspect of healthcare, from the clinician decision support system (CDSS) administered through electronic medical records for aiding in diagnosing and treatment planning to virtual assistants for healthcare professionals. Specifically, it has been widely applied in various aspects of healthcare such as computer-aided diagnosis systems, medication guidance, intelligent Q&A, augmentation of medical images, and socially assistive robots in hospitals. Sophisticated algorithms that can address the idiosyncrasies and noise of various datasets will enhance the reliability of the prediction model[29]. Federated learning allows hospitals to collaboratively learn from a shared medical predictive model while maintaining all data in each hospital, thus preserving privacy of sensitive health data [28]. AI systems have reached expert-level diagnostic accuracies, leading to a promising future with affordable healthcare services that benefit a larger population[27]. AI also has the potential to triage clinical workflow, freeing up time for physicians and allowing them to concentrate on more sophisticated tasks and patients who require specific attention[22].

We believe that AIoT will ensure affordable healthcare services with improved treatment outcomes for patients and develop fine-tuned workflows with better performance for healthcare providers and patient experiences.

2.3 Development of AIoT technologies in healthcare

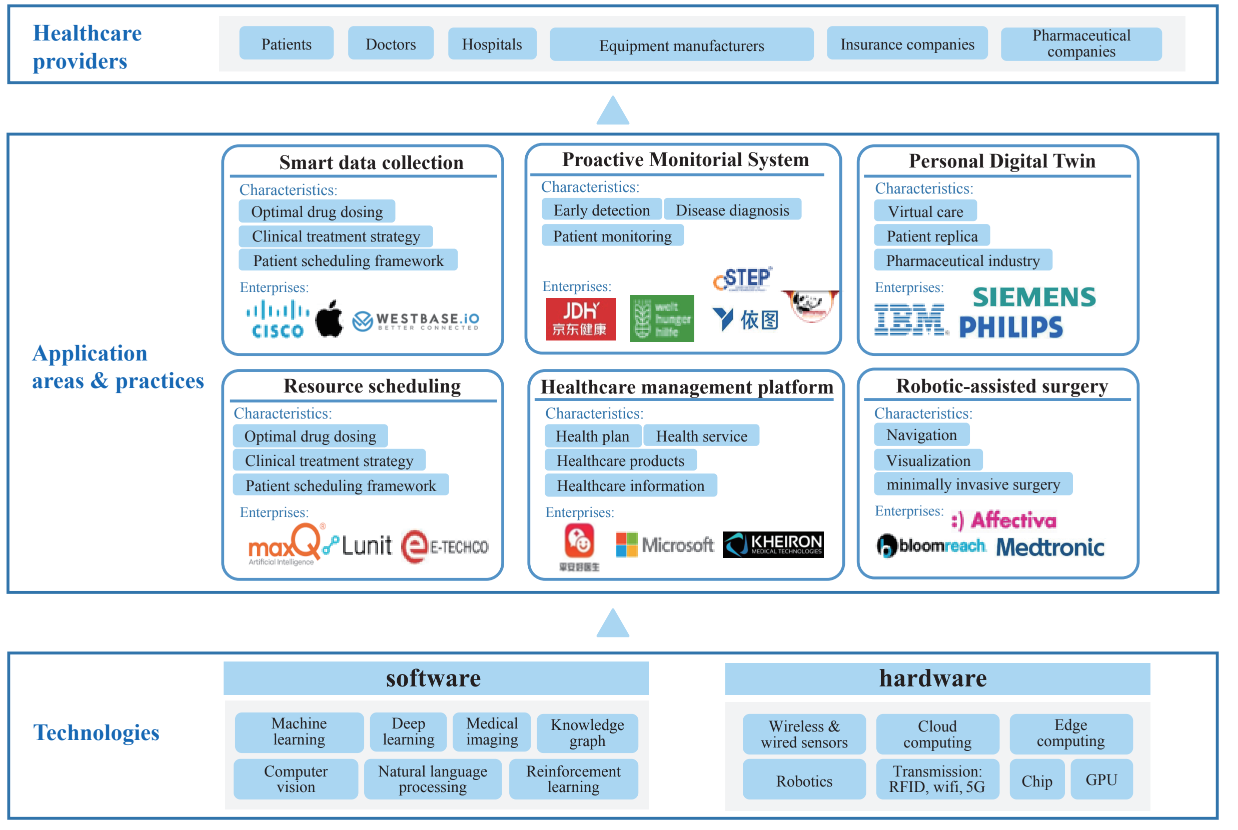


Figure 4 Architecture of AIoT in healthcare

In the last decade, the development of AIoT technologies in healthcare greatly promoted the consolidation of industrialization in healthcare. According to reports by MarketsandMarkets, the global AI in the healthcare market was valued at about USD 4.9 billion in 2020 and is projected to be USD 45.2 billion by 2026, at a CAGR of 44.9% from 2020 to 2026; while, the IoT in the healthcare market size was USD 72.5 billion in 2020 and is expected to grow to USD 188.25 billion by 2025, registering a CAGR of 21% during the forecast period.

Figure 4 depicts the architecture of AIoT in the healthcare industry, which involves three perspectives, i.e., technologies, application areas and practices, and healthcare participants. As we can see, by combining both AI (e.g. machine learning, deep learning, and computer vision, and others) and IoT & Infrastructure (e.g. sensors, 5G transmission, Robotics, and others) technologies, enterprises such as Microsoft and IBM in North America, Medtronic and Kheiron Medical in Europe, and JD Health and Qure.ai in Asia pacific have moved steadily onward into healthcare. Prevalent AIoT application areas include smart data collection, proactive monitorial systems, personal digital twins, medical resource scheduling, healthcare management platforms, robotic-assisted surgery, and many more. Those applications bring tremendous benefits for patients, doctors, hospitals, equipment manufacturers, insurance companies and pharmaceutical companies. Chapters 3 and 4 will study some of those areas in detail and analyze successful application cases, each with its main characteristics, enterprises, and types of participants involved in it, and its benefits, and challenges.

2.3.1 A brief survey

Below, we provide a brief survey on the development of AIoT technologies in healthcare.

The history of AI technologies can be traced back to the 1970s, when advancements in computer technologies made it possible to scan and load medical images into an electronic device. Limited by computing power, medical image analysis of that era could only deal with low-level pixel processing, such as edge filtering[34] and region growing[35]. To judge a person's health status, many if-then-else rules were designed to construct a compound expert system[36], which is popular in artificial intelligence but often fragile. In general, the first step of AIoT into healthcare was a rule-based system and was a far cry from anything resembling automatic diagnosis.

Since the human-designed rules cannot cover all possible situations and often can only weakly predict health status, it is imperative to model the rules. Therefore, at the end of the 1990s, machine learning techniques were proposed to train a model with feature vectors extracted from labeled data, which replaces rule formulation with active learning. In other words, models can be automatically optimized in a high-dimensional feature space. Furthermore, the concept of feature extraction could be a critical step in promoting the discriminant information acquisition of medical images. However, this process is still conducted by manually designing extraction methods.

The next breakthrough point, intuitively, should be to learn feature representation via deep neural models. As deep learning algorithms develop, models are designed with multiple layers and optimized following an end-to-end fashion, which directly transforms input data (e.g. images) to outputs (e.g. disease present/absent). During the process, increasing higher-level features are learned layer by layer, laying the foundation for optimally representing the data for particular tasks. Recently, an abundance of deep learning methods [37-41] have been proposed to offer more accurate health diagnoses, such as tumor detection, continuous glucose monitoring, and protein analysis.

As for IoT & Infrastructure technologies, there are three crucial factors: perception, communication, and calculation. Perception denotes the ability of AIoT devices to obtain various indicators of the human body through different sensors. As part of AIoT, sensor technologies have developed rapidly over the past twenty years, from the thermistor to one detecting blood oxygen saturation, which has greatly enriched the available types of reference indicators and provided the necessary information for healthy diagnostics. After data collection, various communication technologies (e.g., Bluetooth, Wi-Fi, and LTE) are then leveraged to transmit these user data to computing centers where diagnoses will be conducted, and corresponding results will be sent back to end devices. However, such a centralized architecture, aiming at providing an unthinkable amount of computing power for each end device, suffers two significant challenges: high latency of information feedback and online interconnection of massive devices. To meet these challenges, on the one hand, a new-generation communication technology, fifth-generation mobile networks (5G), has been designed and used, with the characteristics of high speed, low latency, and massive bandwidth. On the other hand, the concept of edge computing has been proposed, which refers to an open platform that integrates core capabilities of the network, computing, storage, and applications. Take health care robots as an example. They not only need to respond quickly to the doctor's remote instructions and send the patient's condition back to the doctor in real-time but also need to ensure the patient's life safety under any circumstances (such as sudden power outages). These calculations must occur on the device side instead of in the cloud.

2.3.2 Key areas of AIoT in healthcare

In the healthcare sector, AIoT enables cost-effective and reliable services for real-time health monitoring, whose key areas could be demonstrated as follows:

Data collection is the first step toward health diagnosis. Recently, various sensors (e.g., EEG, ECG) and smart devices (e.g., smartphones and smartwatches) have been developed to provide the potential to obtain diverse and comprehensive physiological data.

Status monitoring aims at continuously monitoring the user's physiological status that may indicate a risk of disease. This technology allows people, in time, to discover health issues that could drastically affect their daily life and work.

Intelligent diagnosis and prevention play a supporting role in assisting doctors with diagnosis or provide reliable diagnosis and prevention methods to patients in areas where medical resources are scarce. Health organizations concentrate on building a systematic healthcare system and allocating medical resources intelligently, thereby improving resource utilization efficiency and reducing expenses.

A closer look at four key areas of AIoT technologies in healthcare

3.1 Smart Data Collection: IoT technologies for effective collection and analysis of data in health

3.1.1 Literature review

This section provides a comprehensive review of the Smart Data Collection system where IoT technologies are used for effectively collecting and analyzing health data.

Concurrent with the growing consciousness of healthcare, there has been an increase in the demand for healthcare services such as remote health data collection and monitoring. Clinicians and providers must design smart data collection systems to increase efficiency. Due to the large amount of data churned out by the healthcare industry, it is critical to collect and analyze data in real-time and build healthier communities around preventative care.

As introduced in Chapter 2, IoT is a system of interrelated computing devices, mechanical and digital machines, and objects that are engineered to have the ability to collect and transfer data over a network without requiring human-to-human or human-to-computer interaction. With the advent of IoT technologies in healthcare, we see technologies pushing the envelope on what we can truly achieve in this area to improve system performance as well as quality of life[42]. Specifically, IoT has brought cost-effective and reliable service for real-time health monitoring, efficient addressing of emergencies, and also provided personalized care for patients. Below, we review the literature on IoT systems from four aspects, namely data collection, data transmission, data processing, and solution.

Data collection lies at the bottom of the IoT system. It refers to the process of using end devices to collect massive amounts of health data, which comes from many sources and includes various data types. A variety of literature focuses on dealing with the collection of sophisticated data types in IoT in order to provide a flexible, reliable, and low-cost service for users. Prior implementations utilize micro-controllers such as Arduino and Raspberry Pi to collect physiological data from specialized sensors (e.g., EEG, ECG) and then a PC-based environment [43-46] to further process and analyze the collected data. Recently, many projects have leveraged advanced hardware devices (e.g., smartphones and smart-watches) to enhance the varieties and volume of healthcare data [47].

Data transmission is implemented at the center of the IoT system, which forwards sensing data from each end device to the server. The transmission link between end devices and servers is commonly wired and/or wireless [44]. Applications, such as minimally invasive surgery [4] and robotic surgery [46], employ wired transmission to meet the requirements of lower response time and high reliability. Compared with a wireless link, the data suffer less interference and noise during wired link transmission. However, the wireless link is favorable in massive IoT networks and dynamic environments. Recent work on wireless sensor networks includes developing novel energy-balanced routing methods [48-53].

Data processing is implemented in different platform tools and aims to process and analyze data after the data transmission. Depending on the needs of end-users, there are two types of computing platforms, i.e. edge computing, which processes data at the nearby edge server, and cloud computing which processes data at the cloud server with high computation capacity. Leveraging AI techniques, IoT has the potential to analyze health data by deriving new and important insights from the vast amount of data generated during the delivery of healthcare every day[56].

Solution refers to the delivery of results or commands to end devices and offer specific solutions to different problems. Many efforts from academia and industry have been made to provide high-quality solutions for healthcare services. The work in [54] explains the process of remote monitoring, data storage techniques, data processing, and data transmission methods, along with the hardware and the software required for practical healthcare problems. Health-CPS is designated for patient-centric healthcare applications and services based on cloud computing and big data analytics [55]. Westbase.io from the UK provides primary 4G LTE healthcare solutions that help make the operations more efficient and deliver outstanding patient services.

3.1.2 Analysis

The aforementioned studies have confirmed that with the advent of IoT technologies, health data can be effectively collected and analyzed, thus enabling it to be further leveraged in medical practice for decision making (e.g. choosing clinical options), anomaly detection, etc. IoT improves the ability of medical devices and has provided intuitive access to robot-assisted surgery. For instance, minimally invasive surgery recently garnered increasing popularity because it offers patients benefits such as higher accuracy, faster recovery time, reduced pain and scarring, compared to traditional open surgery. Besides, real-time data collection and analysis techniques in IoT enable improved care, accelerated workflows, and better patient experience. However, there still exist some challenges in IoT, especially for healthcare applications.

Security of devices. IoT security encompasses several aspects ranging from physical layers of sensors, computation and communication, and devices to the semantic layer in which all collected information is interpreted and processed. The lowest security at any level determines the overall security, which may result in the leakage of users' privacy.

Reliability of IoT devices. Healthcare applications are highly time-sensitive and critical due to the impact that an error may have on, for instance, patient safety or information confidentiality. Malfunctions of supporting IoT devices (e.g., wearable medical devices) failing to capture critical data, any network outage, data corruption, or loss during transmission or storage may have catastrophic consequences, such as mission failure, financial loss, and/or harm to users.

Resource management. In healthcare applications, data collection and transmission require a large number of end devices whose power and communication resource are usually limited. To fully utilize the IoT capacity, it is crucial to prolong the life of IoT networks by improving the efficiency of device power consumptions and network communication resources in IoT.

In conclusion, IoT can act as a supplemental approach to enhance the efforts of human treatment by providing medical services for patients, such as health monitoring and activity prediction. However, efforts such as security, reliability, and resource management still need to be put into achieving the full potential of IoT in healthcare. With the development of IoT techniques, there will be more innovation and higher-quality applications.

3.2 Proactive Monitorial System: AI technologies for early detection, disease diagnosis and patient monitoring

3.2.1 Literature review

This section provides a detailed review of the Proactive Monitorial system where AI technologies are leveraged for early detection, disease diagnosis, and patient monitoring.

Healthcare everyone and is vital to our everyday lives. Due to the increasing demand for care and the complexity of data in healthcare, while scarce availability of human experts and fatigue among healthcare workers is leading to delay and mistakes in diagnosis, our healthcare system is struggling with inefficiency, ineffectiveness of medical image understanding, and inadequate time for clinicians with patients, etc. Therefore, it is urgent to transform healthcare in many ways, such as early detection for early intervention, disease diagnosis for assisting clinicians, and patient monitoring for alerting caregivers to critical events at an early stage.

Machine learning (ML) is a branch of AI that focuses on training algorithms to make classifications or predictions and discover patterns and insights in large data sets, which subsequently drives decision-making within applications. Machine learning has the potential to provide data-driven clinical decision support to physicians. Recently, deep learning (DL), a subfield of machine learning, extracts useful patterns or features from data in an automated fashion. It eliminates some of the manual human intervention required and enables the use of large datasets. At the heart of DL, algorithms are neural networks that reflect the behavior of the human brain, allowing computer programs to identify patterns in data. In particular, convolutional neural networks (CNNs) are a class of neural networks that are commonly applied to process and analyze visual imagery. CNNs are effective tools for image interpretation and can be applied to medical images for diagnosis and prognosis through segmentation and detection methods. Below, we review the AI technologies for early detection, disease diagnosis, and patient monitoring, respectively.

Early detection of diseases before the patient exhibits any symptoms by using AI technologies is vital for dramatically improving patient outcomes. The sooner a person can diagnose a disease, the more quickly it can be treated, ideally leading to better outcomes. The importance of early detection cannot be overstated. For example, coronary artery disease (CAD) is the buildup of plaque in the arteries, which supplies oxygen-rich blood to people's hearts. A heart attack could result from a narrowing or blockage of the coronary arteries caused by plaque. Chest pain and shortness of breath are common symptoms. Early detection and treatment of CAD are vital for patients. Gabor-CNN (Gabor-Convolutional Neural Network)[57] was proposed as a deep learning algorithm for early CAD detection on ECG data and had the potential to assist clinicians in screening for cardiovascular disease. Asthma is a chronic inflammatory disease of the airways of the lungs, causing breathing difficulties and wheezing, etc. It affects people of all ages and can become life-threatening. Thus, early detection of asthma is urgently needed. [58] Awal M A, et al. proposed a novel Bayesian optimization-based machine learning framework for asthma (BOMLA) detection. The experimental results show that BOMLA can detect asthma with high accuracy and can also be used for real-time asthma detection.

Disease diagnosis often involves medical images acquired by devices such as MRI, CT scan, or mammograms of patients' organs. With the rapid development of deep learning technologies, new methods are being designed to help clinicians to interpret MRIs and scans and assist them in high-precision diagnosis. Below, we review the applications of deep learning methods in diagnosing diseases, including fatty liver and Alzheimer's disease. Fatty liver is a term that describes the buildup of fat in the liver. The increasing prevalence of overweight and obesity has led to a surge in fatty liver disease associated with the risk of serious health problems such as diabetes and high blood pressure. [59] Che H, et al. leveraged a multi-feature guided multi-scale residual convolutional neural network model on ultrasound image dataset for nonalcoholic fatty liver disease classification. It shows an average classification accuracy above 90% on ultrasound images data. Alzheimer's disease (AD) is the most common cause of dementia associated with symptoms of the ongoing decline of brain functioning that affects memory and thinking skills etc. [60] Nigri E, et al. proposed a deep learning method that interprets AD by producing a heat map depicting the brain regions using MRIs of the brain. [61] Amini M, et al. presented a new neural network model to diagnose the severity and stage of AD, which achieved high classification accuracy.

Patient monitoring is designed to help clinicians make informed decisions and reduce variation in care delivery due to the immense demands on clinicians. By analyzing patient data using advanced AI technologies, the patient monitoring system can identify and alert clinicians to critical events at the earliest possible stage. Obstructive sleep apnea (OSA) is a relatively common sleep breathing disorder, and the degree of sleep apnea is assessed by the apnea-hypopnea index (AHI) evaluation index. Huysmans D, et al. [62] designed a convolutional neural network for sleep-wake classification based on healthier patients (AHI<10). OSA patients are tested based on the mean confidence in sleep prediction. Diabetes is a chronic condition where one's blood glucose level is too high due to abnormal production and/or absorption of insulin. Common symptoms include increased thirst, increased urination, feeling tired, and losing weight. Malik S, et al. [63] developed a machine learning prediction framework that finds hidden features of underlying diabetes. The model can predict whether a patient is diabetic or non-diabetic based on diabetes data.

3.2.2 Analysis

AI technologies offer a real opportunity in healthcare to automate some of the medical processes, including early detection, disease diagnosis, and patient monitoring. It helps medical professionals make earlier, faster and better decisions and improves the outcomes and cost of care. However, there are still several challenges for applying AI to real-world medical scenarios.

Disease Complexity. In actual medical diagnosis and treatment, conditions associated with certain diseases can be very complex due to different symptoms, causes, and environments. AI models that solve problems as simple classification tasks will not work when applied to diseases with complicated conditions. Thus, the question of how to use AI to assist the diagnosis needs to be further explored.

Shortage of medical data. Machine learning algorithms require a large amount of data for training. The training process of the models can be seriously affected due to the shortage of high-quality medical data. At present, a large number of cases do not have follow-up results as control, so it is often impossible to judge whether the diagnosis of AI models is accurate.

Gap between tests and real-life clinical environments. There is still a big gap between the test environment and the actual medical environment. For example, the recognition rate of a certain type of disease model can reach 95% on the test set but immediately falls to 70% or even lower when applied to the clinic.

To conclude, AI technologies provide promising results for early detection, disease diagnosis, and patient monitoring. However, how to collect high-quality medical data and narrow the gap between test and actual clinical environments need to be studied to overcome substantial challenges. As technologies advance, AI will transform healthcare in many ways.

3.3 Personal Digital Twin: Digital twin system customized as a patient replica or virtual care

3.3.1 Literature review

This section provides a detailed literature review on the Personal Digital Twin system, which is customized as a patient replica or virtual care.

The concept of the digital twin was first proposed by Grieves in 2003 [64][65]. With researchers deriving some new insights related to the digital twin[66][67], the comprehensive definition is given by[67]as an integrated multiphasic, multiscale, probabilistic simulation of an as-built vehicle or system which mirrors the life of its corresponding twin. The digital twin is a digital replica by modeling the state of a physical system, which reflects the data obtained from sensors into digital media. It builds a bridge between the physical and digital world and makes predictions for the future.

Known from various studies in the field of engineering[71] the digital twin has many applications in various branches in the field of healthcare [72]. In particular, a patient replica is constructed using the data collected by the sensor and usually works as the digital organ model of a digital twin. Meanwhile, as a crucial application for digital twin, virtual care has been defined as the interaction between patients and their circle of care, occurring remotely, to enhance the quality of patient care.

In this paragraph, we briefly review the digital twin in healthcare from several practices, including digital patients, the pharmaceutical industry, and virtual care. In the creation of digital patients, large amounts of data from patients and advanced simulation tools are used to generate digital organ models using technologies related to biomedical, mathematics, bioengineering, and computer science. By building up integration between the local physiology and the systemic physiology of the patient, the wider effects of the disease and potential interventions can be simulated. Several advanced models were proposed: the digital brain known as The Blue Brain Project which aims to solve the structure and connections of the human brain and transfer it to the computer. The heart model by Philips[73] that is motivated by the question of whether it is possible to discover and treat ailments in the human body before they occur, and Siemens Healthineers which produces intelligent algorithms that can generate digital organ models based on large quantities of data. As for the practice in the pharmaceutical industry,   it uses Digital Twin technology to see the interaction of an organ with medicines which can reduce the activities of testing medicine trials on animals. As for virtual care practice, the high dimension novel data-driven healthcare system based on AI technology provides a conceptual framework for the creation of "virtual patients" or "digital twins", while individual patterns of disease are paired with digital models that dynamically reflect the status of the disease state [70].

3.3.2 Analysis

There are some interesting applications for digital twins. In the field of health, the US Army with the University of Nevada creates virtual twins of soldiers. Digital twins of soldiers are created using various imaging techniques. The organs of soldiers can be produced by the 3D printing method by using models in Digital Twins when they get injured. For another example, in the radiology department of Mater Private Hospitals in Ireland, by digital twins, Siemens Healthineers finds that with 50 minutes more hours of work per day for MRI, personnel costs can be reduced, and 9,500 Euros per year can be saved. Although a great many digital health devices have been used that aggregate health information and collect patient-reported outcomes [68], many new innovations do not demonstrate that technology-enabled care is safe and cost-effective, seamlessly integrates into workflows, or does produce outcomes that are data-driven, leading to a general lack of adoption of virtual care [69]. The challenges of digital twin can be listed below [74]

Design Considerations and Desiderata. It includes clear data visualization, ease of access and accessibility, ease of adding and removing data sources, integration into clinical workflow, standardizing digital twin methods, and interoperability protocols.

Ethical Implications of Human Digital Twins. Pattern identity of digital twins might result in unacceptable segmentation and discrimination. Therefore, governance mechanisms should be introduced to safeguard the rights of individuals, protect personal biological information, and foster transparency of data usage.

1.https://www.epfl.ch/research/domains/bluebrain/
2.www.siemens-healthineers.com
3.https://www.3ds.com/press-releases/single/dassault-systemes-livingheart-project-reaches-next-milestones-in-mission-to-improve-patientcar/

Finally, utilizing a large number of medical Internet of Things devices and Digital Twin, we can improve data efficiency. Having access to a larger set of patient data which is collected by IoMT sensors, Digital Twin can use the sets to model the impact for different therapies, personalization, or targeted approaches and develop better-personalized care plans. It can build digital models in virtual space, creating accurate virtual and real mappings which are similar to the real things in physical space in regards to state and behavior. Therefore, by utilizing the visual sensor, artificial intelligence chip, deep learning algorithms, and digital twin modeling technology, early warning and comprehensive care for family members' health can be achieved. Additionally, Digital twins reduce service costs, improve the quality of home health services, and realize the intelligent management of family health, especially for the promotion and reform of the pension industry. It can be said that the digital twin will have a revolutionary significance.

3.4 Medical Resource Scheduling: Reinforcement learning technologies for effective medical resource matching and optimization

3.4.1 Literature review

This section provides a detailed review of the medical resource scheduling system, in which reinforcement learning technologies are leveraged to match and optimize medical resources effectively.

Medical resource scheduling has recently attracted increasing attention due to limited healthcare resources while patients' high demand for them. In a medical system, there are many types of resources to schedule such as patients' admission, operation rooms, diagnostic devices, drug dosing, nursing resources, etc. The medical system needs to design an effective resource scheduling system to reduce costs and enhance accessibility and improve quality. Due to dynamic demands and complex constraints in healthcare scenarios, it is very challenging to solve the problems of medical resource scheduling efficiently in an acceptable timeframe.

Reinforcement Learning (RL), a subfield of machine learning, aims to learn a policy from the interactions between agent and environment with labeled samples. In each time step, the agent exploits the current policy to select an action to conduct based on the current state. And then, the environment returns the corresponding reward signal to update the agent's policy. RL is well suited for systems with inherent time delays, and it tackles sequential decision-making problems that sample, evaluate, and feedback simultaneously. Moreover, compared to traditional methods, RL can construct reasonable policy directly based on experience collected during a learning procedure, not requiring a well-represented mathematical model of the environment or an array of sophisticated heuristic strategies. The above features make RL a natural and excellent solution for medical resource scheduling.

Recent developments in RL for medical resource scheduling have rapidly advanced. Many studies have been conducted investigating the schedule of multiple medical resources, including patients, drugs, and treatment. Below we review some related work. A patient scheduling framework based on the Advantage Actor-Critic reinforcement learning algorithm was developed in[75], which can decrease patients' waiting time. Chang et al. [76] proposed an RL-based algorithm that schedules strategically-timed medical resources to jointly minimize the measurement cost and maximize predictive gain, using dueling deep Q-network to learn a policy dynamically dependent on the health history of patients. To address resource limitation and network congestion problems in clinical decision support systems, a decentralized, federated framework integrating double deep Q-network and mobile-edge computing was proposed in [77]to attain a clinical treatment policy. Padmanabhan et al.[78]applied RL technology to achieve optimal adaptive control for the continuous infusion of a sedative drug to maintain a sedation demand, which aimed at providing optimal drug dosing for an iteratively updated control solution. Based on deep Q-networks, a patient scheduler for Emergency departments in hospitals was designed in [79]to optimize medical efficiency, adapting to dynamic changes of the resources' availability and patient composition. These RL-based algorithms outperformed traditional heuristic-based methods and improved clinical outcomes and service quality, as demonstrated in simulation experiments.

3.4.2 Analysis

RL technologies have discovered the potential of developing satisfactory solutions in medical resource matching and optimization. Despite RL's efficient performance, several challenges and barriers must be surmounted when applying them in real-world environments.

Complexity of the real-world. In the practical environment, resource scheduling decision-making is often confronted with complicated requirements, such as dynamic services, various devices, diverse constraints, and consequence assessment. How to consider them is a necessity for researchers to develop algorithms.Modeling of Policy Learning. The first step of using reinforcement learning is to model problems as a Markov decision process. Collecting and preprocessing proper medical data for state representation, designing a comprehensive reward function, and choosing an appropriate exploration strategy are extremely important, which determine the performance of the RL agent's policy. Interpretability of RL technologies. Although excellent success has been made in solving challenging problems with RL, the policies learned are unable to comprehend the correlation between data features and specific actions, resulting in lacking interpretability. Without guaranteeing stability and security, these limits impede the applications of RL technologies for safety-critical domains, including healthcare [80].Integration of Prior Knowledge. The prior knowledge in healthcare domains is usually professional and reliable, which is beneficial to improving performance. Integrating them into RL-based scheduling algorithms is considered a must for reasonable solutions.

To conclude, RL technologies offer a prospective way to improve the efficiency and quality of medical resource scheduling. However, more theoretical and technical studies are required for surmounting substantial barriers that remain. As theories and applications advance, there is no doubt that RL technologies can be applied in more medical scenarios and obtain more effective performance.

Practical applications of AIoT in healthcare

Since the application of AIoT in genetic sequences in 2018, the commercialization of AIoT healthcare treatment has gradually formed. According to the Reports and Data, the global AIoT healthcare market is estimated to grow from USD 60.83 billion in 2019 to USD 260.75 billion by 2027. In the regional landscape, North America including the US, Canada, and Mexico held the largest healthcare market share in 2018, followed by Europe including Germany, UK, France, etc. North America is forecast to register a CAGR of 28.6% through 2027 due to increased patient consciousness and engagement, which has led to an increased demand for remote care. Meanwhile, the Asia Pacific including China, India, Australia, and Japan, etc. is anticipated to grow at the highest rate and is expected to witness a growth rate of 20.5% through 2027 due to the rising chronic disease patient population, supportive governmental rules, and increasing demand for cost-effective disease treatment.

This section aims to present a variety of successful application cases of AIoT for healthcare in China, India, and other regions in the world. Our selection of practical applications covers a wide range of the key areas of healthcare presented in this white paper, providing solutions addressing prevention, early detection to treatment. Meanwhile, it is also important to focus on different types of participants in healthcare, such as the users, the patients, and the health professionals. As such, the applications below include remote users or patient monitoring, infectious disease surveillance, precise diagnosis, health data management, and robot-assisted surgery, etc.

4.1 Successful applications in China

In recent years, AIoT has been transforming China’s healthcare industry. The applications of AIoT technologies in healthcare are increasingly prevalent in China, and significant progress has been made in many segments of healthcare, including health wearables and management, auxiliary diagnostics and treatment, telemedicine, and hospital management, etc. According to a report by EqualOcean, the market size of China’s healthcare was CNY 7.9 billion in 2020. Specifically, Chinese tech giants, including Tencent, Ping An, Baidu and JD, etc. are accelerating their pursuit of the healthcare market and are starting to hone their strategies on specific corners of the ecosystems. Meanwhile, a large number of startups focusing on subdivisions are also gaining momentum. There are a total of 129 Chinese AIoT based healthcare startups (i.e. iFlytek, YITU, and SenseTime) with three main application scenarios including, namely, medical imaging, medical records analysis, and virtual assistants. Below, we briefly outline the healthcare products and initiatives of Chinese companies. The wide application of wearable devices, such as Xiaomi Mi Band (Xiaomi Corporation, 2010), plays an important role in monitoring patients' health. Mi Band has brought portable medical data detection to heart rate detection, sleep monitoring, and blood oxygen detection. At the same time, medical imaging is also an important way to shed light on an illness. The company applied advanced deep learning and computer medical image analysis technology, combined with high-quality medical data and precipitation of high-level medical skills, developed an efficient and accurate medical image auxiliary system. For instance, Tencent MIYING (Tencent, 1998), an AI medical imaging product released by Tencent, uses deep learning technology to study and train various medical images such as an endoscope, molybdenum target, ultrasound, CT, MRI, pathology, fundus photography, OCT, etc., and carry out tasks such as early screening of major diseases. IMSIGHT (Imsight Technology, 2017) is another such company. Their products and services cover many fields such as radiation, pathology, and radiotherapy. To aid medical diagnosis, Shukun Technology (Shukun Technology, 2017) independently developed the world's leading medical AI neural network, and launched digital doctor products such as "digital heart", "digital brain" and "digital chest", providing intelligent diagnosis and treatment solutions for critical human diseases such as heart disease, stroke, and cancer. Deepwise’s (Deepwise, 2017) flagship product, the Dr. Wise AI medical auxiliary diagnosis system, also covers the nervous system, cardiovascular system, respiratory system, sports system, women's care, and children's care. Moreover, a complete medical service platform can provide undifferentiated high-quality medical services for medical institutions and individuals at all levels. Based on medical data structure and medical knowledge maps, Baidu Lingyi Zhihui (Baidu, 2000) Technology Middle Platform builds several specialized medical capabilities, covering many links such as clinic, scientific research, management, and patient service, and supporting various solutions in and out of the hospital. SenseCare (Sensetime, 2014), the intelligent diagnosis and treatment platform, is Sensetime’s solution. It is dedicated to providing AI intelligent applications covering the complete workflow of diagnosis, treatment, and rehabilitation for different clinical directions. Research on robots is also experiencing a wave of interest. Broadcare Robot (Broadcare Robot, 2015) focused on high-end medical robots and medical automation technology services, including intravenous drug dispensing robots and medical service robots. On the other hand, the complexity of medical terms is also an important reason that hinders its understanding, and many companies have made efforts to address the issue. Atman (Atman, 2016) has been engaged in the research of core technologies such as natural language understanding, machine learning reasoning, and autonomous learning for a long time. The company provides intelligent medical translation, medical writing robots, knowledge maps, and other innovative medical intelligent services for customers in the medical field, thus greatly shortening the information processing cycle and reducing the information processing cost. Malgo (Malgo Algorithm Technology, 2017) is another such company that releases the value of medical texts through algorithms. Its information extraction engine, TROIS, can automatically process various medical texts, including electronic resumes, medical literature, medical treatment guidelines, etc., and extract the key information at high speed and accuracy. Based on the medical knowledge map and inference engine, any medical term can be mapped to the corresponding standard term.

This section presents three successful application cases which are focused primarily on the areas of healthcare consisting of remote patient monitoring for chronic or infectious diseases, accurate diagnosis, and intelligent robot assistants. These include case 1 of infectious disease home monitoring system by JD health; case 2 of children's medical health intelligent service platform by YITU healthcare; case 3 of the online healthcare service platform Ping An Good Doctor by Ping, An Healthcare and Technology.

4.1.1 Case 1: JD Health-RIDMS

The remote infectious disease monitoring system (RIDMS), a mobile app developed by JD Health, aims to provide contactless and senseless remote monitoring and danger alerting services for patients with diseases of the respiratory system and to improve their quality of life.

Respiratory infectious disease is among only a few common causes of patients visiting a doctor. It is an extremely harmful type of infectious disease; according to statistics, there are more than 18.9 billion infections each year. The disease is mainly spread through the air and is highly contagious, vulnerable people such as children and the elderly appear to be most at risk.

The idea of RIDMS was to use hardware technologies of millimeter-wave (mmWave) radar sensors and AI technologies and to combine them into a system monitoring the patients with disease of the respiratory system and making well-informed decisions. Specifically, as shown in Figure 5, the system is composed of several key components. The first key component is the mmWave radar, a remote wireless sensing technology with exceptional advantages of immunity to environmental conditions. Based on this particular intelligent sensing technology, the system provides remote monitoring for patients with disease of the respiratory system and supports detection of heart rate, basic vital signs of respiration, cough and shortness of breath. As a second key component, the system supplies cloud dashboards that give the decision-makers (i.e. health professionals) access to easy-to-understand curated data for notifications and insights in real-time. This at-a-glance system enables the health professionals to manage the patients no matter where they are, thus saving precious time and allowing them to focus attention on other urgent needs. Meanwhile, it also enables patients to access medical services at home. As a third key component, cutting-edge AI algorithms are employed to analyze and detect complex respiratory conditions through the collected data and then send alerts when detecting imminent problems. In particular, algorithms can predict EDD events under disease conditions hours or even days in advance, which provides early intervention to patients, promotes their health and enhances emerging competencies. Furthermore, based on the analysis of historical data by AI algorithms acquired over days, weeks, or months, the system can provide vital information about patients' respiratory and cardiovascular conditions to track and assess the progression of their conditions and the effectiveness of their treatments.

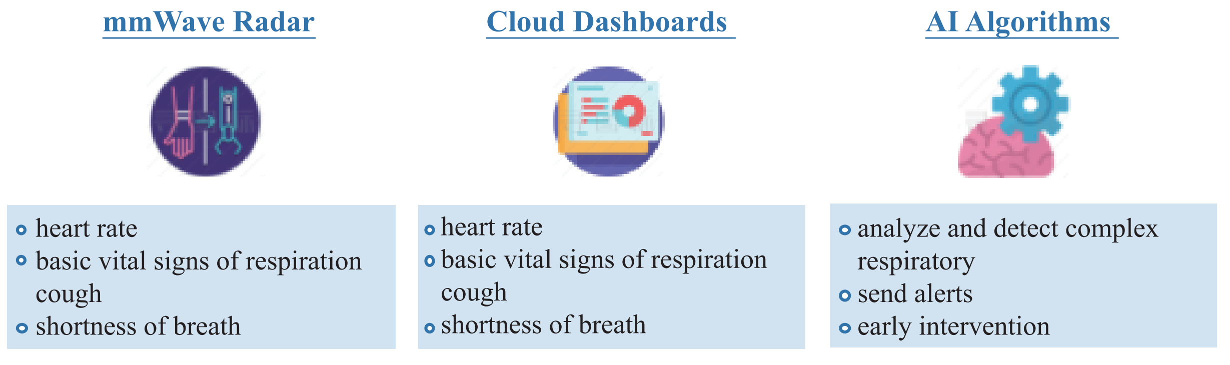


Figure 5 The remote infectious disease monitoring system

Overall, RIDMS is a simple and cost-effective system that enables patients to monitor their heart rate and vital signs of respiration in real-time. Moreover, it provides the health professionals efficient management of patients anywhere and anytime. With this at-home service, professionals' time is largely reduced and the shortage of medical resources is resolved.

4.1.2 Case 2: YITU healthcare-CMHIP

The children's medical health intelligent platform (CMHIP) was developed by Hangzhou YITU Healthcare Technology Co. Ltd, a pioneer in AI innovation founded in 2012, targets to promote the intelligence of the process for accurate assessment, precise diagnosis, and efficient health management for children with pediatric diseases.

The platform is a transformation of a scientific research achievement that was published in Nature Medicine and completed by YiTU healthcare, Guangzhou Women, Children's Medical Center, and other institutes from the US jointly in 2019. The idea was to implement cutting-edge natural language processing (NLP) technologies in diagnosing children's pediatric diseases based on their electronic health records (EHR) containing the medical and treatment histories of patients. Figure 6 depicts the workflow of this platform, which consists of several steps. The first step is data collection. With a novel and automatic collection process, a total of 1.36 million high-quality electronic text medical records from 567,000 pediatric patients has been collected and the final format of data types includes symptoms, signs, laboratory data, and PACS reports. The second step is NLP model construction. This is accomplished in several steps: lexicon construction according to the library of guidelines and consensus, tokenization by Mecab tool, word embedding based on the generated lexicon, schema construction consisting of physician curated question-and-answer pairs for diagnosis, and sentence classification based on LSTM. Applying the trained NLP model to the collected data transforms the data into fully structured data in query-answer pairs. The third step is the hierarchical multi-label diagnosis model. Specifically, an anatomically based classification system was employed for the diagnostic hierarchy. For example, the diagnoses were separated into general organ systems (e.g. respiratory, neuropsychiatric, or gastrointestinal), in each of which there was a subdivision into subsystems (e.g. upper respiratory and lower respiratory). In summary, by automatically learning the diagnostic logic from a large amount of data, this platform can analyze and infer certain conditions of the disease.

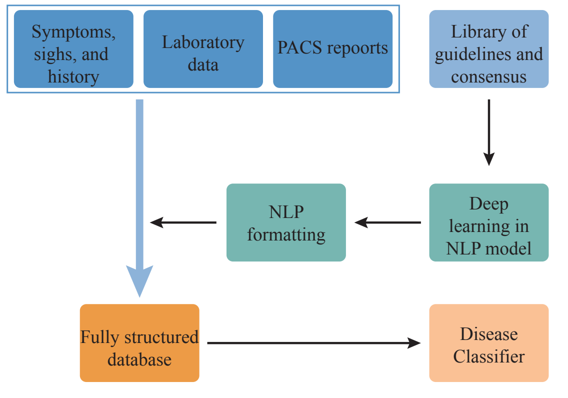
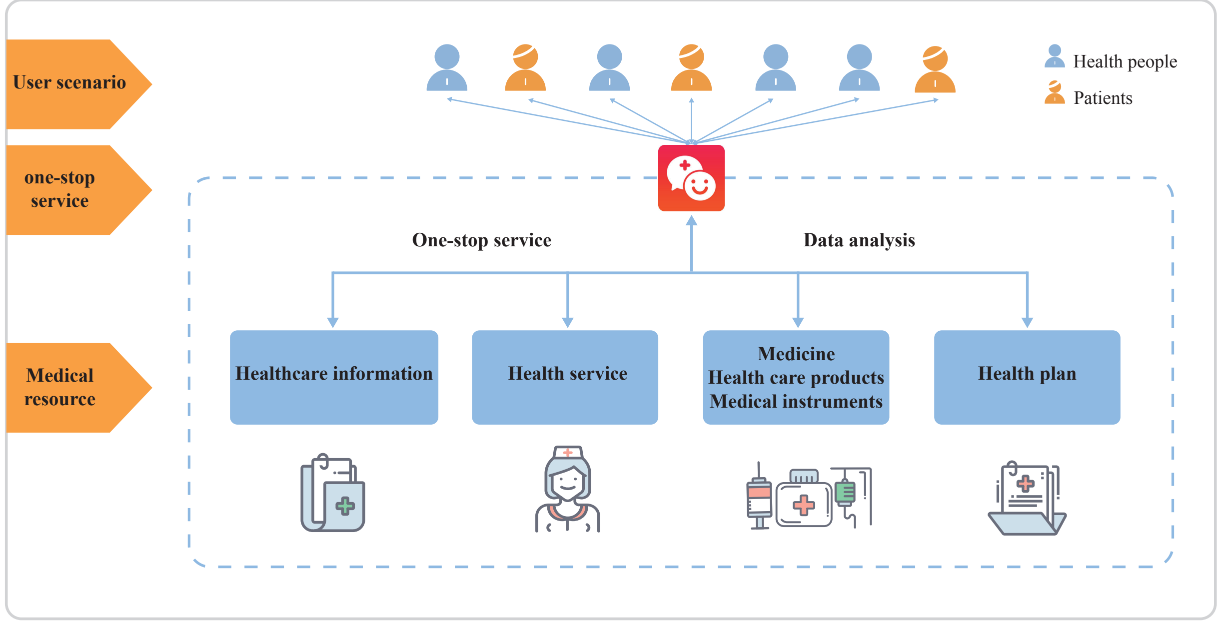


Figure 6 AI to diagnose pediatric disease

In summary, this system has demonstrated the ability to "read" textual medical records of common pediatric diseases like a human physician. Experimental results show that it can reach the professional level of a trained pediatrician-in-chief, with a high accuracy rate of comprehensive diagnosis in common childhood diseases.

4.1.3 Case 3: Ping An Healthcare-Ping An Good Doctor

Ping An Good Doctor, a health mobile platform launched by Ping An Healthcare and Technology Company Limited, provides real-time professional consultation, health management services, one-to-one family doctor services, and additional outpatient with doctor resources.



Source: www.pagd.net

Figure 7 One-stop healthcare platform of Ping An Good Doctor

The idea of Ping An Good Doctor was to leverage doctor resources and a variety of AI technologies including knowledge graph, computer vision (CV), ML, and NLP into a one-stop health consultation and management service for users. As shown in Figure 7, there are four core functions of this platform: healthcare information, health service, healthcare products, and health plan. For the first core function, healthcare information, an intelligent robot based on NLP technologies such as text classification is constructed to classify questions asked by users or patients on the platform. It provides patients with accurate guidance, registration, and intelligent triage, and reduces labor costs for hospitals. At the same time, based on the patients' queries, hospitals are capable of knowing and understanding patients' needs and optimizing hospital management better. The second core function, health service, provides patients with a variety of standardized service schemes, which integrates services of medical and health institutions, preventive and insurance-related needs, etc. For instance, it uses CV and OCR technologies to analyze patients' electronic medical records (e.g. medical history, diagnoses, and radiology images) to hierarchically allocate the right medical resource and guide patients to find the right physician for treatment. The third core function, healthcare products, employ DL and NLP technologies to analyze clinical cases and provide automatic and accurate medical and health products for users such as healthy nutrition, medical devices, and fitness products. It has the characteristics of pharmaceutical e-commerce, convenient medical product purchase, and fast delivery, effectively integrating online and offline services, thus improving efficiency. The fourth core function, the health plan, uses ML algorithms to analyze the patients' recovery conditions or users' health conditions to make personalized recovery plans (e.g. recommended activities and nutrition) or health plans (e.g. diet and calorie intake per day). Furthermore, there is a community on the platform where patients or users can communicate with people having similar symptoms and conditions for resource support and spiritual comfort.

As the leading online healthcare service platform in China, Ping An Good Doctor has formed a commercial closed loop from online medical services to healthcare services due to the virtue of its self-established professional medical team, the transformation of Ping An insurance users, and AI technologies assistance. Clearly, internet healthcare services have become part of the new form for residents when it comes to seeking medical consultation. Currently, Ping An Good Doctor boasts more than 400 million registered users, which has achieved the largest number of active users, and the largest profit scale on the Internet medical platform. The compound annual growth rate (CAGR) of user registration, monthly active users and, daily online consultation volume has increased each year steadily.

4.2 Successful applications in India

In this section, we present successful case studies in India with a special focus on pre-/post/ante-natal care, cancer, and digital healthcare. Throughout all stages of pregnancy, it is imperative to ensure that both mother and child are healthy. The National Family Health Survey 2015-16 highlights that only 16.7% of women in rural India received full antenatal care. According to UNICEF, every day, approximately 830 women die from preventable causes related to pregnancy and childbirth. The majority of these cases occur due to a lack of regular health check-ups (BP, ECG, BMI), fetus development, identification of anemia, and others. This causes unhealthy baby growth and maternal death in India. Early detection and its corresponding treatment are necessary for avoiding emergencies. To this end, there are multiple initiatives focusing on one or more parameters to monitor the mother and child during pregnancy. To broaden the scope of this article, without loss of generality, we direct our attention to the specific cases of malnutrition and anemia. Our choice of biasness towards the two mentioned diseases is due to the fact that they are unfortunately common maladies among the general masses, irrespective of rural or urban locations. Additionally, hygiene and unhealthy lifestyles are also an issue in certain households, which opens the scope for suffering from cancer. India is one of the leading countries in tobacco consumption (both smoke and smokeless), leading to mouth, lung, culinary, and other forms of cancer. Due to poor hygiene and early marriages in India, women often suffer from cervical cancer diseases. Breast cancer is also a common occurrence that needs immediate attention. These conditions cut across all social-economic groups across India. The Government of India (GoI) is actively taking part in overcoming these challenges and we highlight some of the prominent initiatives. Telemedicine and remote consultations such as eSanjeevani require the constant attention of doctors and caregivers. Additionally, the patients should also be able to convey their illness in a proper manner. ML-based routines have the potential of bridging the gap between the physical checkups and that on the online mode. For instance, the Mayelin Foundry Pvt. Ltd. (Mayelin Foundry Pvt. Ltd. 2021) offers the integration of AI/ML-based routines on audio, video, voice, and sensor data, particularly for edge devices. With the proliferation of IoT devices and their configurations, such targeted solutions are necessary for facilitating ease of use. Such solutions offer insights on the patient's condition from the captured video frames to the doctor. The doctor may then make suggestions based on the conversation, his experience, and inputs from the ML-based assistant. Conversely, the same model may be used to monitor the fatigue of the doctor herself and set reminders for refreshment or for some stretching between consultations. For diagnosis, companies like Qure.ai (qure.ai 2016) provide ML-based solutions for identifying illness in chest X-Rays and CT scans of both head and chest. They are also working on developing models for producing ultrasonic images. Another important aspect of telemedicine is chat-bots. Sigtuple (Sigtuple 2015) is another such company. They focus on the analysis of blood samples, microscopy, fundus, OCT scans, and chest x-rays, and many others. They are excellent proxies to use in situations when the doctor is not available and also to generate an initial report. Further, the chatbots may also be used to match the patients to the concerned doctors. One of the chatbots that is gaining popularity in India is the Zini App (Grainpad 2020) by Grainpad. Zini is an AI-powered bot that discusses the whole scenario in detail to identify the problem and make suggestions accordingly. Wysa (Wysa 2021) is another such chatbot that focuses on providing support to the mental health of the patients. Apart from the behavioral and health analysis, automated methods for scheduling consultation meetings are also important. The time and duration based on the patient's condition and availability of both parties (patients and doctors) are necessary parameters for consideration. Towards this, solutions such as those offered by Appointik (Appointik 2017) are beneficial. Another important requirement is the digitization of prescriptions. In rural areas, exposure to digital media and the use of personal computers is uncommon, which increases the challenge of migrating important information (from physical to digital platforms). A straightforward solution may be to capture images and store them. However, analyzing these images and making inferences from the content is important for easy interpretations. Solutions pertaining to image processing, particularly image to text such as in (Chattopadhyay et al. 2020) may be useful. The mentioned solutions are not only useful in the eSanjeevani setup but also on the different components of NDHM (refer to Section 4.2.3 for details). In the context of patient monitoring, solutions pertaining to video-based surveillance and tracking are helpful. Towards this, companies such as Igzy (Igzy 2011) play a vital role. They offer video-based surveillance backed with strong ML routines for ensuring regulatory compliance, child safety, hygiene management, fire and line safety, intrusion detection, proximity monitoring, access control, forensic evidence, and many others. Further, video processing-based ML solutions such as COVI-SCANNER (Deb et al. 2021) help in monitoring and maintaining the sanitization of the hospital areas. In summary, the scope of AI and ML-based solutions in the government initiatives for adopting automation and digitization is significantly high. Both industries and academia are investing this area. In summary, we present three case studies: 1) malnutrition and anemia, 2) cancer and 3) government initiatives.

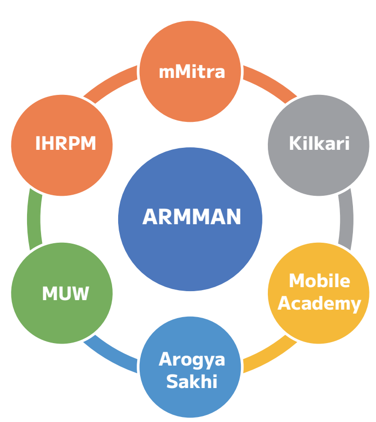


Figure 8 Components of ARMMAN.

4.2.1 Case 1: Malnutrition and anemia

Statistical reports show that up to 68% of deaths of five children under five are due to maternal and child malnutrition (IndiaSpend 2021). The National Nutrition Mission (NNM) in India has targeted to work towards reducing this by 2% per annum. However, access to modern healthcare facilities and early detection of malnutrition in the remote (villages) locations of India is a challenge. To address this issue, the application Child Health Monitor (CHM) by Welthungerhilfe (a German company partnered with India's Action Against Hunger), backed with Microsoft Azure's AI, has developed a seamless method for diagnosing children. The application requires the Anganwadi worker to take a 3D model of the child (subject) by hovering the phone around her. It relies on the inbuilt infrared sensor to calculate generate the 3D model of the child, along with her height, volume, and weight ratio. The application also uses the head and upper arm circumferences of the child (precision in the scale of millimeters). The application collects this information and sends it to the cloud for analysis. The execution of the entire operation takes only a few seconds with minimal training and capital. The Indian non-profit organization ARMMAN (ARMMAN 2008) has been dedicated to the wellbeing of pregnant women along with their children since 2008. As shown in Fig. 8, ARMMAN consists of 6 components. The mMitra offers a free mobile voice call service for providing timely information to subscribed patients. It has provisions for accommodating time slots and language preferences. The Kilkarni and Mobile Academy components offer mobile health education and training, respectively. They are backed with features such as Interactive Voice Response (IVR) to facilitate automation and ease of use. On the other hand, the Arogya Sakhi component is responsible for provisioning women health entrepreneurs to provide affordable healthcare services to mothers, children, and their families. The Moderately Underweight Children (MUW) and Integrated High-Risk Pregnancy Management (IHRPM) offer special services. As the name suggests, MUW enables health trainers to interact with mothers to educate them about taking care of their underweight children. IHRPM trains midwives, nuns, doctors, and medical officers on managing high-risk pregnant patients and tracking them.

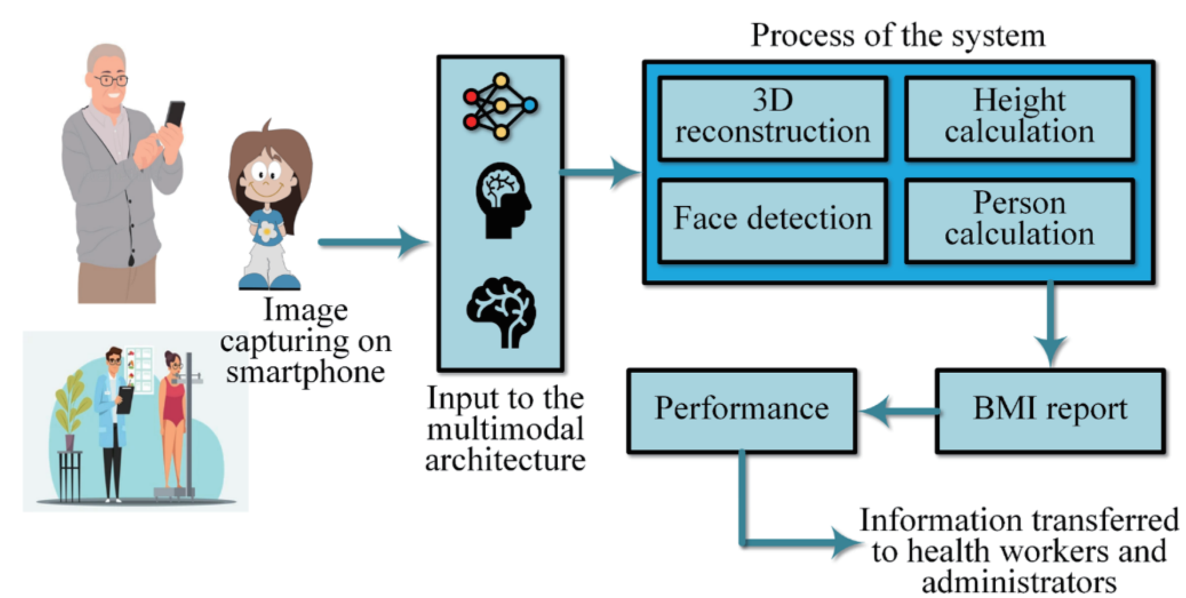
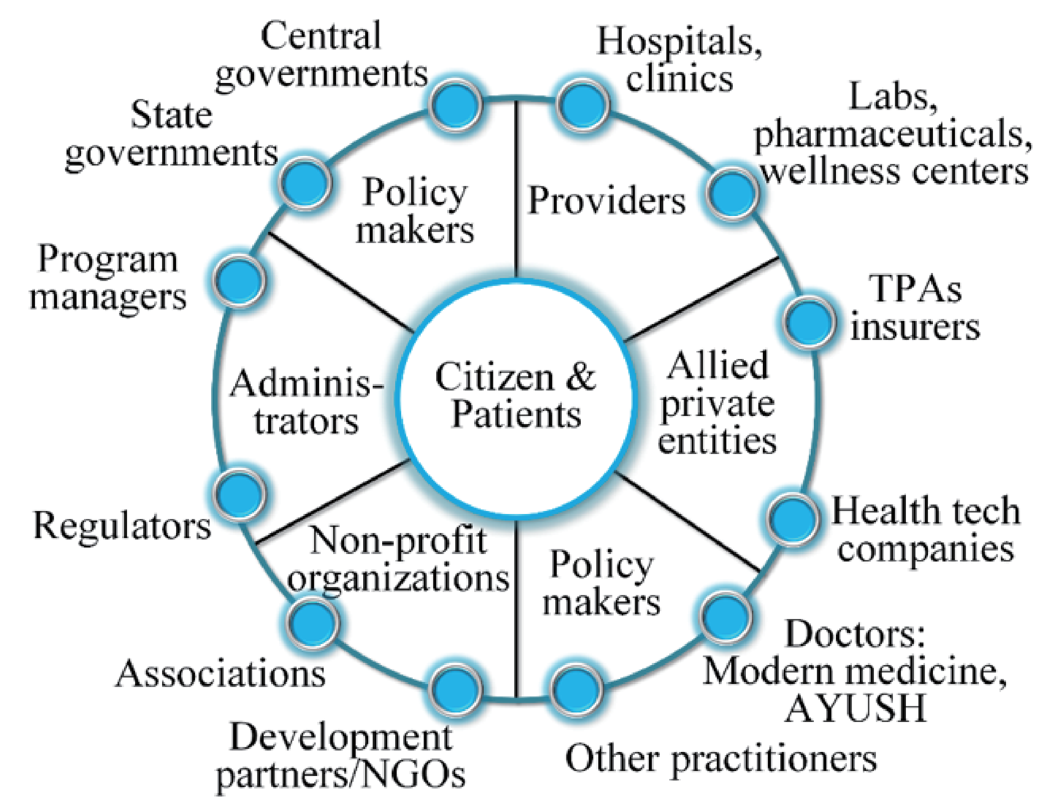


Figure 9 Schematic diagram of AIoT solution for Malnutrition

Another Indian initiative for tracking and monitoring malnutrition among children and infants is the Solution for Nutrition and Effective Health Access (SNEHA) AI toolkit by the Center for Study of Science, Technology and Policy (CSTEP) (CSTEP 2005). SNEHA exploits the features of Information and Communication Technologies (ICT) and AI for calculating height, BMI, and attendance based on images captured through a smartphone. Additionally, it is also capable of detecting anemia. Researchers at Bosch India have also identified the need for anemia detection in areas that lack medical equipment and services. To address this need, they developed a hemoglobin monitor (Financial Express 2021), which is also backed with a state-of-the-art AI solution, and does not require blood tests. On similar lines, researchers at the International Institute of Information Technology, Naya Raipur in collaboration with the All India Institute of Medical Sciences, Raipur have developed a smartphone-based solution to measure blood hemoglobin and anemia (refer Fig. 9 (Ghosal et al. 2020)). Their solution sHEMO (Ghosal et al. 2020) works by capturing the eye image of a person and performing further diagnosis of anemia using onboard AI and image processing.

4.2.2 Case 2: Cancer

With the ongoing demographic and epidemiological transition, cancer is emerging as a major public health concern in India. About 50-60 % of patients with cancer of the mouth, breast, and cervix in India present with advanced disease. The treatment of patients with advanced cancer is very resource-intensive and results in significant morbidity and side effects with poor quality of life. The current guidelines of the government of India for screening include clinical examination of mouth, breast, and cervix (VIA-visual inspection after application of acetic acid). These techniques hold a low level of sensitivity for picking up cancers. In this endeavor, thanks to IoT and AI, provisioning personalized oncology services to the doorstep of patients is feasible. The National Brain Research Institute (NBRC) and Advanced Centre for Treatment, Research, and Education in Cancer (ACTREC) have taken initiatives to recognize AI for healthcare as a major field of study. To cope with the problem of datasets, the NITI Aayog is developing a framework to host a repository of annotated and curated pathological image data. The Government of India is planning to extend the scope of AI for diagnosing cancer and improving the quality of healthcare services through National eHealth Authority (NeHA), Integrated Health Information Program (IHIP), and Electronic Health Record Standards for India, respectively . Among industries, IBM has taken a similar interest in oncology with AI (IBM). They offer suggestive solutions to clinicians and also provide a platform for researchers for conducting experiments. Recently, an Indian-based startup Niramai Health Analytix Pvt. Ltd. has developed an AI-integrated non-invasive and portable cancer screening tool that uses machine intelligence over thermography images to detect breast cancer in women of all ages. The name NIRAMAI stands for Non-Invasive Risk Assessment with Machine Intelligence. As the name suggests, NIRAMAI is radiation-free, painless, and is dependent on an ML-based solution. Another Indian-based company, AiNDRA System (AiNDRA 2021), has developed AI-based computer vision for screening cervical cancer. Their intelligent screening system, CervAstra, is portable and analyzes pap smear samples, classifying the samples as Normal or Cancerous. Further, Sascan Meditech, a startup company in India has built another AI-based optical imaging multimodal device, OralScan for the early detection of precancerous lesions of the oral cavity. On the other hand, researchers at the Indian Institute of Technology Madras have developed NBDriver, an AI-based mathematical model that is capable of identifying anomalies in DNA sequences. They focused on identifying the patterns of DNA sequences (A, T, G, and C) and capturing the uncontrolled growth of cells due to genetic alterations. IIT Kharagpur and Tata Medical Center together have set up a cancer image biobank named CompreHensive Digital ArchiVe of Cancer Imaging (CHAVI) to aid cancer research in the country (IIT Kharagpur 2019). CHAVI is augmenting the computational cancer research scope using artificial intelligence and deep learning methods.



Source: Web[5]

Figure 10 The NDHM Ecosystem

[5] https://www.indiascienceandtechnology.gov.in/sites/default/files/cancer%20story.pdf

4.2.3 Case 3: Government Initiatives for Digitizing Healthcare in India

Owing to the advancements of technology and the rapid adoption of IoT backed with AI/ML solutions, the Government of India (GoI) has started an initiative of its own for developing a common platform for integrated services. In particular, through the National Digital Health Mission (NDHM), the GoI is actively developing a framework to facilitate the seamless integration and information exchange among the different participants (refer Fig. 10[5]) in the country's healthcare ecosystem. This initiative has the potential of bridging the gaps between the different components while providing universal citizen-centric healthcare service. Towards this endeavor, the NDHM aims to provide the following essential features:

- Efficiency
- Accessibility
- Inclusion
- Affordability
- Timely
- Security

The key motivation towards the development of the NDHM is to effectively improve the wellness-centric and wellness-driven efficiency and transparency of healthcare services in a secured fashion, while maintaining consistency and integrity of the data to be shared with different hospitals when required. Most importantly, the crux of the NDHM development is citizen-centric service, which increases accountability of the healthcare providers.

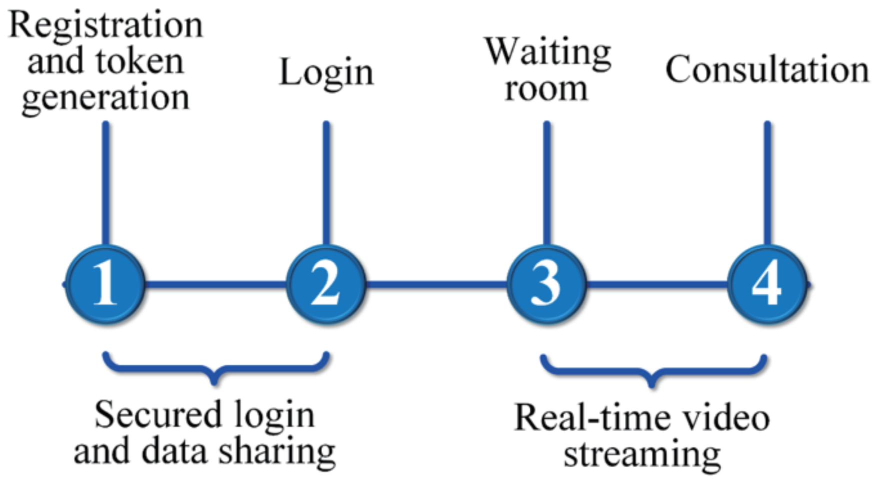


Figure 11 Steps in volved in eSanjeevani

The NDHM typically uses the support of two other application platforms initiated by the GoI: eSanjeevani and Pradhan Mantri Jan Arogya Yojana (PM-JAY). Both initiatives are under the GoI's Ayushman Bharat Scheme. The eSanjeevani scheme was launched in November 2019 as the first online outpatient (OPD) consultation service. It is also termed the National Teleconsultation Service and provides a secured and structured consultation with the doctors for patients from the comfort of their homes. With eSanjeevani being hosted on both desktop and handheld devices, it has found attention from a large audience, inclusive of both rural and urban setups. For ease of usage, the doctors and concerned panels are handled by the state government. In summary, with respect to healthcare services, the eSanjeevani platform bridges the gap between rural, urban, financial status, and other social strati. Fig. 11 highlights the key features of the eSanjeevani platform, which includes patient registration, audio-video consultations, and doctor's recommendations. These are achieved via SMS/Email notifications, Real-Time Streaming (RTS) protocols, scheduling algorithms, and other relevant protocols/routines. In times like the recent COVID-19 pandemic, platforms like eSanjeevani are of paramount importance.

[5] https://ndhm.gov.in/home/ndhm

The PM-JAY on the other hand is a health insurance scheme. It is inclusive of expenditures in primary, secondary, and tertiary healthcare services. Since the plan is targeted towards to poor and rural communities of the country, it has a list of criteria to be fulfilled for an individual to be under this scheme. In addition, the Ayushman Bharat Scheme also has developed multiple Health and Wellness Centers throughout the country, mainly for primary healthcare services. The fusion of the Ayushman Bharat Scheme, eSanjeevani, and NDHM, together with solutions backed with AI/ML routines, has significant potential for turning around the quality of healthcare service in India.

4.3 Successful applications worldwide

The increasing prevalence of AIoT in the global healthcare industry has revolutionized patient healthcare worldwide. In 2018, the global spending on AIoT initiatives was nearly USD 646 billion, with high investments by hospitals for medical care. In particular, the market growth is driven by the increasing adoption of AIoT technologies in various healthcare applications, with a focus on medical imaging, disease diagnostics, health data management, robotic-assisted surgery, and drug discovery. In the landscape of the other regions in the world, North America (e.g. US) and Europe (e.g. Germany and UK) account for the largest two shares. Big companies - Microsoft, IBM, Medtronic, Alphabet, Facebook, and Apple have been aggressively infiltrating many healthcare sectors and some of their endeavors have the potential to change healthcare at large. As big companies move steadily onward into healthcare, there is a large number of startups (i.e. Kheiron Medical, Roam Analytics, and Atomwise) working on applications such as health management, medical imaging, drug discovery, and medical records management. Below, we briefly outline the healthcare products and initiatives of companies worldwide. Amazon (Amazon, 1994) has been aggressively infiltrating as many healthcare sectors as possible over the last few years. Amazon is setting up initiatives to transform pharmacy, the medical supply chain, health insurance, and care delivery. It is also leveraging its delivery power to carve into the medical supplies distribution space and using its massive employee base to test the telemedicine field. Medical equipment also has a niche. Apple (Apple, 1976) has been boosting the number of health-related features accessible on its Watch to establish the wearable as a clinical tool to be used in medical research. Furthermore, Binah.ai (Binah.ai, 2016) can transform any device equipped with a simple camera into a medical-grade healthcare gadget. Health data also includes medical images. Subtle Medical (Subtle Medical, 2017) has developed a suite of deep learning software solutions that enhance images during the acquisition phase of the radiology workflow, improving workflow efficiency and patient experience. SubtlePET and SubtleMR bring the latest imaging enhancement technology to existing scanners. On the other hand, biomedical raw data formats will bring difficulties for traditional ML. BioSymetrics (BioSymetrics, 2015) solves this problem by deploying its primary solution, Augusta. Augusta begins with diverse, raw medical data types (e.g. images, chemical structures, genomic data, tabular data), and operates across three modules: Pre-Processing, Machine Learning, and Architect. For diagnosis, InformAI (InformAI, 2017) supports artificial intelligence in image classifier and patient outcome predictor, which can speed up medical diagnosis at medical points and improve the work efficiency of radiologists. Another company, Remedy Health (Remedy Health Media, 1994), equips non-physician staff with clinical expertise through an AI-assisted platform. Early diagnosis allows them to find the best fulcrum point for intervention to positively affect health outcomes. Furthermore, in precision medicine, Alphabet (Alphabet 2015) takes advantage of its dominance in data storage and analytics to patch up interoperability challenges and streamline clinical research.

Drug research certainly plays an important role in the medical field. NVIDIA (NVIDIA, 1993) helps drug research and development with an accelerated computing platform. Whether one is searching the molecular database, storing massive data or simulating the complex biochemical reaction process between molecules and the human body, the solution supported by NVIDIA has helped pharmaceutical companies to improve their analytical ability, data processing efficiency, and scalability. From the model design, Owkin (Owkin, 2016) combines life-science and machine learning expertise to create models that predict disease evolution and treatment outcomes. These predictive models are used for enhanced analysis, surrogate endpoints, patient stratification and selection, and subgroup identification. Drug development and clinical trials combined with AI are more targeted and cost-effective.

This section reports three successful application cases that are focused mainly on areas of healthcare including medical imaging for breast cancer, health data management, and robotic-assisted surgery. These include case 1 of Microsoft Cloud for Healthcare by Microsoft in the US; case 2 of Mammography Intelligent Assessment by Kheiron Medical in the UK; case 3 of Hugo robotic-assisted surgery (RAS) system by Medtronic in Germany.

4.3.1 Case 1: Microsoft-MCH

Microsoft Cloud for Healthcare (MCH), an intelligent platform developed by Microsoft in the US, aims to provide healthcare organizations the capabilities to manage health data at scale for better patient experience, coordinate care, and operational efficiency.

The platform employs AIoT technologies including machine learning (ML) and CV, to improve patient experience and care. Specifically, as shown in Figure 12, it contains three primary features, i.e. enhances patient engagement, empowers health team collaboration, and improves clinical and operational insights. The first primary feature is that it enhances patient engagement which includes the following aspects: personalized care to build relationships via enhanced experiences, patient insights that transform data into prescriptive insights, and virtual health that uses AIoT to provide new avenues for remote care. The second primary feature is the empowerment of health team collaboration. It consists of three aspects: care team coordination that uses ML algorithms to optimize hospital resources, care collaboration by developing systems of engagement with intelligent workflows, and continuous patient monitoring that implements AIoT for better treatment. The third primary feature is the improvement of clinical and operational insights. It includes data interoperability that creates new healthcare systems by connecting data from multiple systems of records, operational analytics for optimizing operations, and clinical analytics to securely assess data.

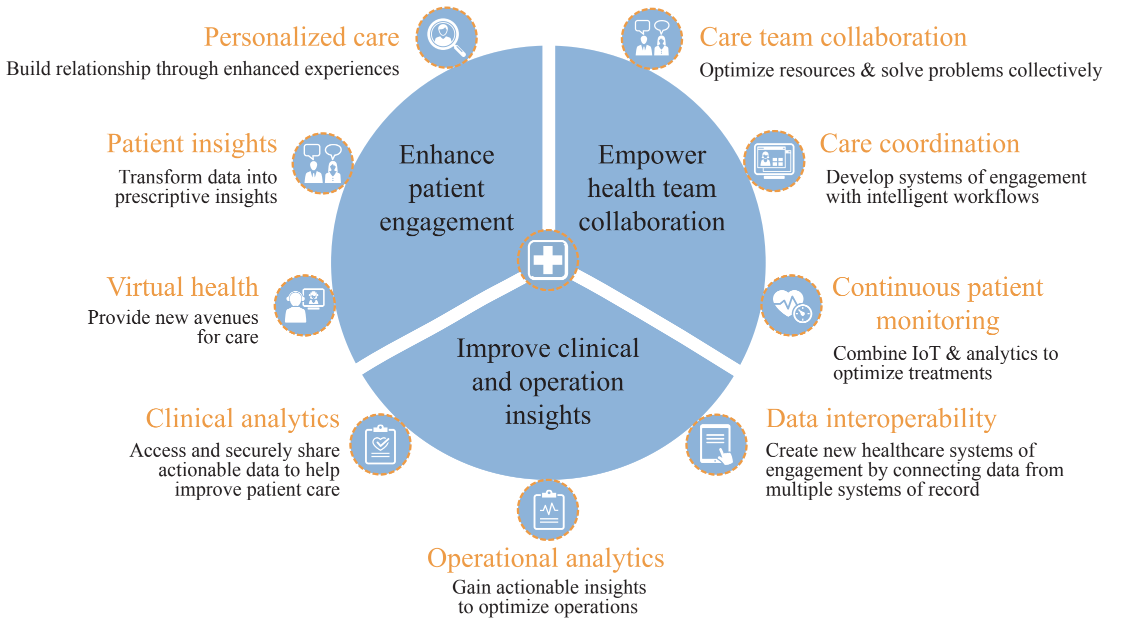


Figure 12 Microsoft Cloud for Healthcare System

Source: Web[6]

Overall, this system enables health data to flow securely across every procedure of care to improve patient experience and health outcomes. It is also capable of connecting clinical and operational data through different systems to optimize operations and improve patient care. Moreover, the system accelerates the health team's ability to coordinate care securely with intelligent workflows.

4.3.2 Case 2: Kheiron Medical-Mia

Mammography Intelligent Assessment (Mia), the first Conformitè Europëenne (CE) certified AI product developed by Kheiron Medical in the UK, aims to help breast-screening professionals detect breast cancer at earlier stages of the disease and improve patient outcomes.

[6] https://www.microsoft.com/en-us/industry/health/microsoft-cloud-for-healthcare

According to the World Health Organization, 685,000 deaths are attributed to breast cancer globally, and 2.3 million women were diagnosed with breast cancer in 2020, making it the worlds' most prevalent cancer. Mia is designed to empower radiologists and breast screening services to deliver confident, accurate, and timely results using AI to any woman, anywhere. With cutting-edge AI technology developed on more than 3 million images, Mia is designed to assist breast-screening professionals in deciding whether to recall women for further testing based on their mammography screening. Its workflow consists of three steps: Case sources, Truthing, and Outputs, as shown in Figure 13. In the first step, all of the cases come from the UK/EU screening population in double reader European programs. This means that two radiologists interpret each mammogram and the third is involved only when there is no consensus between the two readers. The cases are all 2D FFDM images produced from multi-vendor devices. In the second step,all cases have been classified with ground truth evidence: positive cases were chosen with proven pathology results obtained from the surgical decision, and negative cases were chosen based on having no evidence of cancer during screening interval or at the next screening round. In the third step, for each case, Mia provides the following outputs. For positive cases, Mia provides case-wise and side-wise recall suggestions and an explanatory Region of Interest (ROI); for the negative cases, Mia provides suggestions not to recall.

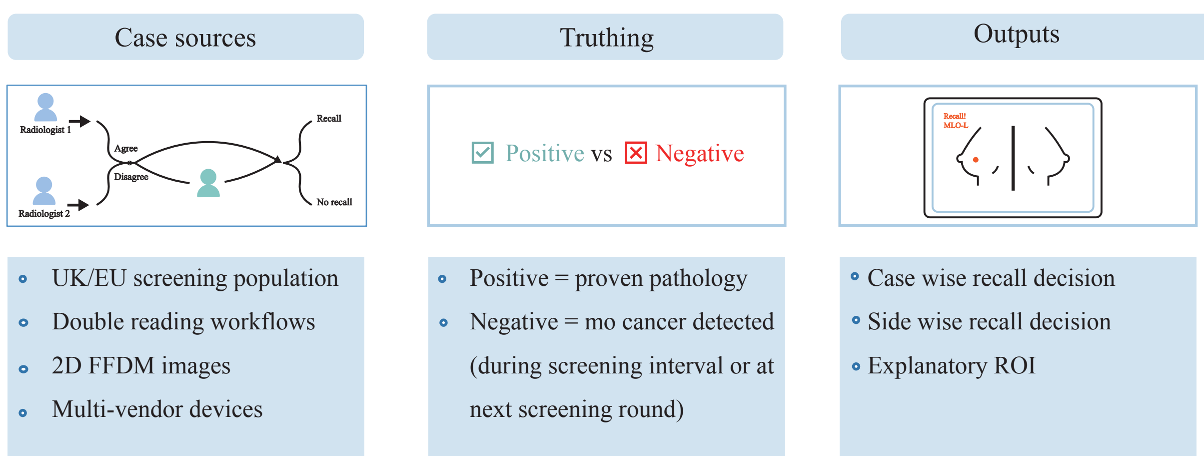


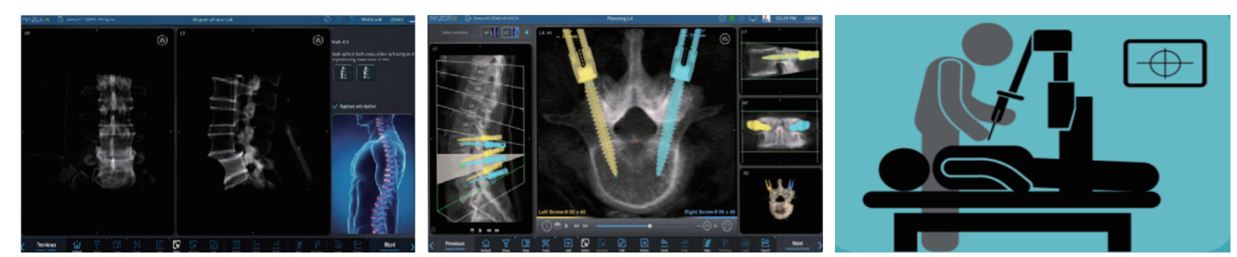
Figure 13 Mia for breast cancer detection

Mia has been proven in one of the most ambitious clinical studies in radiology AI to date and has been tested across multiple demographics and mammography devices. Specifically, it was evaluated across 275,000 cases from seven sites in the UK and Hungry. In addition, Mia is brought to the Health Services across Northern Ireland and the Republic of Ireland, which makes a new milestone for AI adoption in the breast screening community.

4.3.3 case 3: Medtronic-RAS

The Hugo robotic-assisted surgery (RAS) system, developed by the global medical device company Medtronic in Germany, is designed to expand access to the benefits of minimally invasive procedures and advance health outcomes for patients worldwide.

RAS augments surgeons' expertise to deliver more effective care and can be used in many procedures such as spine surgeries and kidney removal. Figure 14 depicts a procedure of robot-assisted spinal surgery. During robotic spinal surgery, there are three primary tasks for surgical teams: visualizing, planning, and operating. For the task of visualizing, computed tomography or CT scan of the area where the patient will be operated on is taken by the surgeon, and then a 3D image of the surgical area is generated using the RAS software. For the task of planning, the surgical trajectories are depicted in detail by the surgeon using 3D software. In the case of spinal surgery, details of trajectories include the positions of rods, screws, and other implements. As such, the effect of the planned implants on the spine can be reviewed by the surgeon using the 3D software, which gives the surgeon a window of time to choose the right surgical option and improve the accuracy of the surgery. For the task of operating, a robotic arm is mounted on the bed and an x-ray of the patient is taken by the surgeon. The x-rays are then aligned with the CT scan taken in the visualizing task by the RAS software, which further aligns the surgical plan with the position of the patients. After that, a sheath in the surgical arm guides the robot to make an incision, use a drill, and insert an implant. Throughout the process, the surgeon is guided by watching the software's 3D visualization on a screen. RAS uses advanced visualization technology and can record, store and review surgical videos of the procedure.



(a) Visualizing (b) Planning (c) Operating

Source: MIT Technology Review Insights

Figure 14 Spinal robotic-assisted surgery

In summary, Hugo RAS combines huge sectors of technology such as robotics and navigation into a sole platform which has been shown to provide a higher degree of accuracy. It also helps standardize surgical procedures and enables minimally invasive surgery with less scarring and shorter recovery time, which improves outcomes for clinicians, hospitals, and patients.

Challenges and explorations

5.1 Challenges of adopting AIoT technologies in healthcare

Advances in machine learning algorithms and low-cost tensors have given rise to the healthcare system. This chapter explores the technical challenges and other broader social and ethical considerations for deploying AIoT systems.

5.1.1 Challenges of trust

Trustworthiness of the AIoT healthcare system is critical to achieving the potential of AIoT technology. We consider four separate dimensions of trustworthiness: Data Privacy and Protection, Model transparency and accountability, Fairness and Bias, and Autonomy and stability.

(1) Data privacy and protection
As AIoT systems are developing in healthcare, health data is a key and critical source for AIoT systems to knowledge learning and algorithmic procedures. With the application of AIoT in healthcare, health data including medical and health-related lifestyle data, ranging from individual clinical and public health data to behavioral and environmental data, are being generated and accumulated. However, a significant portion of healthcare data comes from individuals and is particularly sensitive. The collection, use, analysis, and sharing of healthcare data has long been a widespread societal concern. Because of the sensitivity of the data, misuse of private data can both undermine the dignity of individuals and lead to serious problems such as incorrect diagnoses, while the process of sharing or transferring data can potentially make them vulnerable to cyber theft or accidental disclosure. Therefore, data protection frameworks and regulations are critical to managing the use of health data. A data protection strategy is a rights-based approach that includes standards regulating data processing activities, both protecting the rights of individuals and imposing obligations on private and public data owners, collectors, and processors, and including sanctions and remedies for violations of legal rights.

(2) Model transparency and accountability
Most societal concerns about trust are highly related to transparency and understanding what AIoT systems collect, what their purpose is, what they do with the collected information, how they make a particular decision, especially if that decision causes harm, and who is responsible for the harmful decision. Because AIoT healthcare systems directly affect the health and well-being of individuals and the public, AIoT technologies should be understood or comprehensible to all the participants including developers, users, healthcare professionals, patients, and regulators. Transparency requires that sufficient information is published or documented before AIoT technologies are designed or deployed and that this information facilitates meaningful public consultation and debate about the design of the technology and how it should or should not be used. Another way to ensure trust in AIoT systems is through accountability. Accountability ensures that if an AIoT system makes a bad decision, there is someone who can be held accountable, whether it is the hardware manufacturer, the software developer, or the system's machine learning algorithm engineer. In the event of damage, there must be a complete redress mechanism in place so that those who are harmed by a bad decision can be fully compensated.

(3) Fairness and biases
AIoT healthcare systems are designed to encourage the broadest conceivable range of appropriate and equitable use and access regardless of age, gender, income and education level, races, ethnicity, ability, or other characteristics protected by basic human rights. If the datasets used for AIoT systems are not adequately inclusive of people of different genders, races and ethnicities, or socioeconomic backgrounds, the results may be biased. Bias may also be due to the source of the data used to train and deploy the AIoT system. If AIoT systems are initially designed and trained with data from specific local populations with different health conditions, it is unlikely that broadly representative data will be collected. As a result, AIoT systems designed and trained in one country and then applied in another country with a different health profile may be ineffective or provide incorrect diagnoses or predictions for people of different races, ethnicities, or body types. Such bias is a threat to inclusiveness and equity because it can lead to a deviation from the principle of treating all lives equally. Therefore, AIoT healthcare systems should only be deployed if such bias can be mitigated, and the algorithms used in AIoT should be designed to reduce power inequalities and bias. Furthermore, special provisions should be made to protect the rights and welfare of vulnerable or minority groups and to provide mechanisms for judgment and redress when such bias and discrimination occurs or is alleged to occur. In addition to these principles of fairness, AIoT research still needs to support the diversity of researchers working on the project, including those doing the annotation.

(4) Autonomy and stability
The principles of autonomy and stability require that the use of AIoT healthcare applications does not undermine human autonomy and does not displace humans from the center of health decisions. This means that healthcare professionals and experts should maintain full control over healthcare systems, healthcare decisions, and in particular, the authority to forcibly terminate an AIoT system at any time if the expert believes it will cause harm to personal or public health, as well as property. However, it remains questionable how much control, or autonomy, should be permitted to AIoT decision-making systems. AIoT systems should be designed to assist humans, whether healthcare providers or users, in making informed decisions. Human oversight may depend on the risks associated with AIoT systems but should always be of meaning and therefore should incorporate effective oversight of human values and ethical considerations. Respect for human autonomy also requires the associated responsibility to ensure that system providers have the information they need to use AIoT systems safely and effectively and that people understand the role such systems play in their care. At the same time, healthcare authorities, healthcare professionals, and regulators should be involved and engaged in the design of AIoT systems and, where possible, in software engineering.

5.1.2 Challenges of technologies

AIoT can potentially illuminate the healthcare delivery process by censoring recovery-related behaviors, reducing unintended clinician errors, monitoring patients, and assisting the elderly population. We highlight four technical challenges related to multi-source heterogeneous data processing, model capacity, edge computing, and model transferability in the application of the AIoT healthcare system.

(1) Multi-source heterogeneous data

To get the whole picture of complex human conditions, wearable and contactless devices need to monitor a series of different signals, which may be different in formats, sizes, and timestamps. An AIoT healthcare system needs to handle these signals from all kinds of users and environments, so that the data shows characters of large volume, diversity, noise appearance, and heterogeneity. We call this type of data multi-source heterogeneous data. How to manage, process, and analyze this type of data is a great challenge, which needs both the improvement of flexible data infrastructure and the development of new data analytic algorithms.

(2) Model capacity

The AI model is one of the key components in an AIoT healthcare system and is responsible for mapping the sensors' data to corresponding users' behaviors, finding possible abnormal phenomena, and giving feedback. To handle big and very likely multi-modal IoT devices' data requires models with high capacity, i.e., models are capable of learning and benefiting from a growing amount of data and the performance should not be saturated. Furthermore, since the data are unlabeled, the model should be able to learn meaningful feature representation in an unsupervised or self-supervised manner. Large-scale models naturally have a larger capacity, but they could require many days to train even using large clusters of hardware. The inference time of large-scale models is another issue. Although we can speed up the training process of large-scale models by using data-parallel techniques, since the model is essentially a directed computed graph, it is difficult to parallel each component in the computed graph and reduce the inference time for each unit of data.

(3) Edge computing

It is crucial to deploy models on edge devices for real-time data stream processing and preservation of privacy in AIoT healthcare systems. However, edge devices are limited by their energy supply, computational and storage resources. We can design or automatically search computationally efficient and hardware-friendly small models for these devices, but the performance of these models is always worse than their larger and more complex counterparts. Also, the capacity of these small models may be saturated using a moderate volume of data and cannot benefit from larger datasets. One promising approach to solve this issue is to distillate the knowledge from the big models to models suitable for edge devices. How to adaptively convey larger models' ability to these edge devices is of practical value but still remains challenging.

(4) Model transferability

Training large models are very expensive, both in time and resources. Meanwhile, these trained models are performed only on their specific tasks, directly using these models to other tasks may lead to performance decline. Furthermore, in healthcare applications, due to regulations, the cost of data collection and the occurrence rate of a specific illness, the available volume of data may not be large enough to support the training of large models. Therefore, finding the intrinsic relationships between different tasks and enabling knowledge transfer from one task to another is of great importance to not only reduce the training effort but model the rare events.

5.2 Explorations to boost AIoT in healthcare

Breakthroughs in AIoT and low-cost, contactless sensors have given rise to an ambient intelligence that can potentially improve the physical execution of healthcare delivery. This opportunity requires researchers to work closely with experts from ethics to create a trustworthy AIoT healthcare system.

5.2.1 Trustworthy AI

The requirements for trustworthy AI and the practicality of assessment methods have been increasingly strengthened. All countries have noticed that ethics washing is likely to occur if there is no corresponding enforcement mechanism for "soft" constraints such as ethical ones. To cope with the new changes brought about by trustworthy AI, both academia and industry continue to promote innovative research in the fields of data privacy and protection, model transparency and accountability, fairness and bias, and autonomy and stability.

(1) Data privacy and protection

AIoT healthcare systems make judgments based on huge quantities of data. However, both the data transmission method and AIoT models are vulnerable to the leakage of sensitive and private data. Scholars have proposed a variety of customized security techniques for the aforementioned privacy leakage issues, the most prevalent of which being differential privacy and federated learning. Cynthia Dwork [81], an American academic, was the first to suggest differential privacy. It is a key quantitative measure of AIoT systems' privacy protection capabilities. Downsampling, permuting, and introducing noise are examples of methods that may be used to avoid privacy attacks based on this concept. Currently, the differential privacy technique is being used in sections of actual business operations by a few prominent technological businesses. In addition, federated learning [82] initially distributes AIoT models onto user devices, with each user device calculating the gradient of model parameters and uploading it to the central server using its own private data. Then the central server combines the gradients gathered and delivers them to each user device. Finally, each user device updates the model using the integrated gradient. However, the federated learning technique is still vulnerable to private data leaking, according to certain preliminary research.[83][84]

(2) Model transparency and accountability

Theoretical frameworks for some AI algorithms still need to be refined, and research on the interpretability of AI algorithms is still in the early stages. For example, the effectiveness of optimization algorithms on simple AI models such as decision trees and support vector machines has been proven. Despite the vast amount of research on stochastic gradient descent algorithms' great efficacy in improving deep neural networks, the debate continues and the problem remains unresolved. Some experiments have shown encouraging findings in research on how AI models use data characteristics to create predictions. However, the theoretical foundation is yet to be clearly defined. [85]To improve the interpretability of AI models, suggestions from researchers include: designing suitable visualization techniques to aid in the assessment and explanation of intermediate model states; employing influence functions to deduce the influence of training data on the final convergent AI model; Facebook AI Research using the Grad-CAM[86] (Gradient-weighted Class Activation Mapping) method to analyze the data features used by AI models when making predictions; LIME [87] (Local Interpretable Model-agnostic

Explanations) method is used by University of Washington Seattle to approximate complicated black box models locally using basic interpretable models and to investigate their interpretability further. Furthermore, the method can improve model reproducibility by perfecting management mechanisms for model training.

(3) Fairness and bias
To ensure the fairness of AIoT systems in decision-making, researchers have used the following methods: building a complete and heterogeneous data set to minimize inherent discrimination and bias in the data, checking the data set periodically to maintain high data quality, and using algorithms based on quantitative indicators of fairness to reduce or eliminate decision-making deviation and potential discrimination. Individual and group fairness are the two types of fairness indicators that are presently available. Individual fairness and group fairness are measures of how biased intelligent decision-making is towards various people and groups. Moreover, fairness-based algorithms may be roughly split into three categories: pre-processing techniques, in-processing methods, and post-processing approaches. Pre-processing procedures clean the data by eliminating sensitive information, resampling, and other tactics, minimizing data variance. By using regularization terms that may quantitatively express fairness throughout the AIoT model's training phase, in-processing approaches increase model fairness. In black box AI systems, post-processing approaches can improve the fairness of a trained model by modifying its output to decrease judgment deviation.

(4) Autonomy and stability
The AIoT system's stability has garnered a lot of attention and studies. As early as 2012 and 2013, adversarial and poisoning attacks on AIoT models were discovered. The goal of adversarial assaults is to use specially prepared sample data to cause decision-making mistakes in AIoT systems. The goal of poisoning attacks is to impair the trained model's performance by inserting harmful material into the AI model's training data set. Following the conception, adversarial attacks have successively evolved into the fast gradient sign method [88](FGSM), Carlini-Wagner method [89] and projected gradient descent method[90] (PGD). Backdoor attacks arose from poisoning attacks, which developed quickly. Through backdoor samples, a backdoor is injected into the AI system, allowing the system to be hijacked. Poisoning attacks and backdoor attacks are similar in certain ways.

5.2.2 Super deep learning

Super deep learning will lead the next revolution in the industry by effectively integrating data and information from different modalities, different sources, and different tasks to meet new production needs, new application scenarios, new business models, and the transformation of the digital economy. To cope with the new changes brought about by super deep learning, JD Explore Academy (JDEA) continues to promote innovative research in the fields of multimodal machine learning, supermodel, model compression, and transfer learning.

(1) Multimodal machine learning
Models are trained on language and vision data which is naturally multimodal in some domains—e.g., medical images, structured data, clinical text in healthcare. Thus, multimodal foundation models represent a natural way of fusing all the relevant information about a domain and adapting to tasks that also span multiple modes. Multimodal machine learning aims to build models that can process and relate information from multiple modalities. Based on advances in image processing and language understanding, tasks combining images and text have attracted significant attention; academia and industry have done a lot of meaningful work in these areas. A good intelligent diagnosis system should learn the pathological image and the diagnosis certificate given by the doctor simultaneously to give the most reliable diagnosis opinion based on the pathological image or generate similar pathological images based on the case description. In these tasks, natural language plays a key role in helping machines understand the content of images. However, the natural language process also has multi-modal data. To address these problems, JDEA proposed an effective training strategy to rejuvenate the low-frequency information in the raw data, which is robustly applicable to several model structures and language pairs. In addition to text, there is a lot of low-quality, multi-modal medical data in real medical scenarios. Meanwhile, JDEA also has in-depth interaction with JD Logistics. JD Logistics can ensure that some AIoT Healthcare system products and services will be delivered to the user expeditiously, reducing the waiting time and improving the user experience, which provides comprehensive support for the deployment of the AIoT healthcare system.

(2) Super model
AI is undergoing a paradigm shift with the rise of models (e.g., BERT, DALL-E, GPT-3) that are trained on broad data at scale and are adaptable to a wide range of downstream tasks. The importance of the availability of data and the ability to harness it cannot be underestimated. The rise of self-supervised learning algorithms has unlocked the power of internet-scale datasets which would be intractable to annotate by hand. Google's Transformer [91]model architecture leverages the parallelism of the hardware and unannotated data to train much more expressive models than before. Transformer-based sequence modeling approaches are now applied to text, images, speech, tabular data, protein sequences, organic molecules, and reinforcement learning. These examples point to a possible future where we have a unified set of tools for developing supermodels across a wide range of modalities. JDEA also embraces the transformer architecture in both natural language processing and computer vision, using a transformer with cross-lingual position representations to model the bilingually aware latent structure for the input sentence. ViTAE[92] introduces the inductive bias from convolutions into transformers for better feature representation.

(3) Model compression
Supermodels have also led to surprising emergence which results from the scale. For example, GPT-3, with 175 billion parameters compared to GPT-2 's 1.5 billion, permits in-context learning where the language model can be adapted to a downstream task simply by providing it with a prompt (a natural language description of the task), an emergent property that was neither specifically trained for nor anticipated to arise. However, the size of the supermodel also limits its deployment, and transfer learning and model compression allow the supermodel to be deployed on more devices. Model compression refers to removing the redundancy of parameters and feature maps for deep learning models so that they can be well deployed on resource-limited devices. Low-rank approximation and pruning for sparse structures play a vital role in many model compression works. Compared with conventional methods, the recently developed dynamic pruning methods determine redundant filters variant to each input instance which achieves higher acceleration. Most of the work in academia and industry discover effective subnetworks for each instance independently and do not utilize the relationship between different inputs. To maximally excavate redundancy in the given network architecture, JDEA proposes a new paradigm that dynamically removes redundant filters by embedding the manifold information of all instances into the space of pruned networks [93].

(4) Transfer learning
Supermodels have taken shape most strongly in NLP, so we focus our story there for the moment. By the end of 2018, the field of NLP was about to undergo another seismic change, marking the beginning of the era of supermodels. On a technical level, supermodels are enabled by transfer learning and scale. The idea of transfer learning is to take the “knowledge” learned from one task and apply it to another task. Within deep learning, pretraining is the dominant approach to transfer learning: a model is trained on a surrogate task and then adapted to the downstream task of interest via fine-tuning. Since feature structures generally represent the common knowledge across different domains, they can be transferred successfully even though the labeling functions across domains differ arbitrarily. Academia and Industry achieve this by making the student imitate shallow behaviors, such as soft targets, features, or attention, of the teacher. On a technical level, Supermodels are enabled by transfer learning [94]and scale. The idea of transfer learning is to take the “knowledge” learned from one task (e.g., object recognition in images) and apply it to another task (e.g., activity recognition in videos). Within deep learning, pretraining is the dominant approach to transfer learning: a model is trained on a surrogate task (often just as a means to an end) and then adapted to the downstream task of interest via fine-tuning. JDEA proposes Tree-like Decision Distillation (TDD) to distill the decision process from the teacher into the student, which relieves the student of the burden of searching in the solution space[95].

6. Vision and future possibilities of AIoT in healthcare

6.1 A privacy-preserving healthcare data platform

We can try to establish a unified big data platform that can effectively protect the privacy of health data.

Considering the privacy of medical data related to patients and the polymorphism of different data, in the unified health care big data platform, we should focus on building a data security operation platform and allocating different storage spaces for different forms of data for storage and processing. This involves the following acts: (1) regularly carry out data life cycle risk assessment, dynamically perceive data security risks, classify data sensitivity as a dimension, and ensure the visualization of data flow process; (2) provide a trusted verification mechanism for big data access, fine-grained control of big data access, processing, and use, and trusted verification for data providers and data users; (3) analyze the potential risks of data, respond immediately after privacy data leakage, quickly locate the source, form a platform linkage mechanism, and block and dispose of security events.

Certain processing is required before storing the patient's medical and health data, such as desensitization of name, ID card, and other information and setting privacy marks for private data. At the same time, data storage should follow the principle of minimizing time. That is, the storage period of personal information should be the shortest time necessary to achieve the purpose. After exceeding the storage period of personal information, personal information should be deleted or anonymized. Data backup (cloud server) should be carried out regularly, and a disaster recovery scheme should be made.

This paper attempts to use the database system with a searchable encryption audit certificate system to effectively audit the encryption operation behavior of users. At the same time, it meets the requirements of encryption, decryption, verification, and audit of client data. The searchable encryption scheme based on symmetric encryption is adopted. While protecting the behavior privacy of the client of the medical system, it allows the intelligent audit robot to audit data according to the user searchable encryption audit certificate to prevent the client from forging the legal searchable encryption audit certificate, which can ensure the unforgeability. In addition, the method based on a digital signature can be used to realize the integrity and completeness of data, and the encryption authentication scheme can be realized based on a challenge-response mechanism.

At the same time, in the big data storage stage, the storage management of massive data requires us to ensure the security of the data storage environment, which requires us to strengthen the strictness of the default setting operation of the computer system. The access of other client applications to the local database needs to be reviewed and approved by the system operator, As well as the browser's automatic and timely clearing of the cache information collection of the health data web page, as well as the firewall and other isolation means for the database network storing data, to ensure network isolation, and conduct comprehensive and automatic detection and killing of system viruses and Trojans regularly, to ensure the comprehensive privacy protection of the health big data platform from the source, This requires the active cooperation of the operating system provider.

A unified big data platform is inseparable from a comprehensive and coordinated model. Unification means more integration and coordination while ensuring the integrity of the system and the diversification of functions. Therefore, there is the combined application of the trusted artificial intelligence system of the unified big data platform. Trusted artificial intelligence has the characteristics of privacy protection. The training of artificial intelligence models often requires a large amount of data, and the acquisition of this data must go through the steps of collection and storage. In some cases, the collected data sets will be published to a public network. To obtain sensitive privacy information in data, attackers may launch attacks at any stage of data collection, storage and publishing in order to steal data containing sensitive information. For developers of data collection and AI, apart from strengthening the physical security of all aspects of data processing, the most direct way to avoid privacy leakage is to delete sensitive personal information such as name and ID number from collected data, thus making data anonymity. However, this method of directly deleting sensitive information can not completely avoid privacy disclosure. EMAM et al. successfully recovered some user privacy information from anonymous health record data using a method called identity re-identification attack. Specifically, they first obtain other data related to anonymous data through multi-database joint retrieval according to the characteristics of anonymous data and then identify the real identity of a specific individual in the health record by matching the query results obtained from different databases. The above examples show that only anonymizing the data directly cannot completely protect the user's privacy. Therefore, more advanced means are needed to avoid the disclosure of private information from user data. Academic circles have proposed a variety of targeted protection methods for the above privacy disclosure problems, and the most common is the privacy protection method based on differential privacy and federal learning.

The prospect of artificial intelligence in the field of health care is inseparable from the construction and improvement of this credible artificial intelligence system.

6.2 An intelligent integrated medical service based on big data

6.2.1 The need of intelligence in medical services

At present, "Inadequate Medical Services" is still the main point of pain in the domestic medical system. There is a series of difficulties for patients to register and be hospitalized. The number of patients in Third-class hospitals is overloaded, but the restriction of county medical institutions is still very common and the doctor-patient relationship is still tense. In the process of traditional medical diagnosis, doctors mainly rely on their medical knowledge and clinical experience. Therefore, there are some problems, such as uneven diagnosis and treatment level, inaccurate and fine diagnosis and treatment, weak pertinence of treatment scheme, or excessive medical treatment. In particular, due to the non-exchange of diagnosis and treatment information in different hospitals, patients have to carry out repeated examinations or accept repeated medication, which increases the pain of patients and delays the diagnosis and treatment of the disease. Therefore, it is urgent to use big data to establish a patient-centered medical service model, simplify medical treatment links and optimize the allocation of medical resources.

In addition, the outbreak of COVID-19 has raised alarm bells for regulators to enhance supervision effectiveness and respond to public health events on time. In particular, once there is nosocomial outbreak, it will bring huge losses and blows to patients, hospitals, and even the medical system. Therefore, it is urgent to provide a large amount of effective information for regulatory and health departments with big data in a timely fashion to improve their response-ability to public emergencies.

6.2.2 What can big data do

a) Provide doctors with clinical decision-making assistance

Healthcare big data can provide doctors with scientific clinical decision-making assistance. Big data technology supports the establishment of databases such as electronic medical records, biological sample databases, and electronic health archives. Through the establishment of electronic medical records, it can help healthcare providers integrate the data and test reports that can comprehensively and truly reflect the patient's situation and provide doctors with the complete past medical history of patients. At the same time, by comparing with similar data in the database, the intelligent medical system can provide doctors with treatment plan references, medication effect predictions, and adverse reaction warnings. For example, the algorithm can compare the medical image results with tens of thousands of similar effects stored in the database to help doctors diagnose. In addition, the information system can collect efficacy data during treatment. With big data, doctors could compare the effectiveness of treatment measures and provide accurate and effective treatment for patients. Based on big data analysis, it is also possible to develop new drugs or treatment schemes and improve the effectiveness of diagnosis and treatment.

b) Provide health management and disease early warning services to the public

Big data technology can well meet the needs of providing health management and disease early warning services for the public. With the development of science and technology such as gene sequencing and big data analysis, human beings have a more comprehensive understanding of the diseases' pathogenesis, which is convenient for early detection and intervention of diseases. In addition, the public can upload and store their real-time health data, such as heart rate, blood pressure, and sleep status, in the medical database through wearable devices to realize daily health monitoring and analysis. By designing algorithms for disease risk assessment, we can use big health data to calculate individual disease risk, provide disease early warning for the public, and realize early intervention and treatment of major diseases. For patients with chronic diseases and the elderly, big data and health monitoring systems can provide long-term chronic disease management services meticulously and can also seek help in case of emergency.

c) Provide online consultation and optimize the resource allocation of the medical system
Smart medical services use big data to share patients' diagnoses and treatment information among various medical institutions. Doctors can easily obtain patients' complete medical information, while patients can use online consultation, online reservation, and other services. Big data also integrates and shares the high-quality medical resources of medical institutions at all levels, optimizes the allocation of medical resources, and improves medical efficiency. For example, through the comparative analysis of data, we can preliminarily grade the patient's condition, guide the graded diagnosis and treatment of patients, realize the high-quality resource sharing of hospitals at all levels through telemedicine and two-way referral, and then optimize the allocation of medical resources.

d) Provide scientific decision support for regulatory authorities
Using big data systems for data mining and analysis of massive medical data will improve the scientific decision support of health administrative departments. Based on the medical big data system, an intelligent emergency response system can be established to connect and communicate with medical institutions, the local Disease Control Center, and other systems. This system will comprehensively analyze relevant data in real-time and issue forward-looking early warning, which will greatly improve the flexibility and the ability of regulatory authorities to make a timely response when they meet with emergency public health events. In addition, map data and public health data can be used to analyze the distribution of chronic patients and the disabled in order to allocate medical resources more effectively.

e) Alleviate social contradictions and promote harmonious development.
The first point is to reduce the cost of seeing a doctor for patients. Currently, it is difficult and expensive for patients to see a doctor. The repeatability of AI medical treatment can reduce the cost of seeing a doctor and the total time cost of seeing a patient. For example, we often see medical assistants in hospitals or medical robots that can go on the operating table to help doctors perform operations. Medical assistants mainly provide medical consultation and guidance services for patients or help doctors take down patient information. The emergence of medical assistants means patients no longer have to blindly seek medical treatment and enables doctors to say goodbye to repetitive and low-quality work so that they can use their time more effectively and treat more patients.
In addition, AI healthcare can create related social jobs, such as medical data cleaners, AI technology (software and hardware) developers for specific medical problems, AI ethics or governance committees for healthcare, etc. These positions require both specialized AI and medical knowledge, which in turn drives the development of a series of positions through a chain effect.

f) Promote the development of scientific research
In terms of scientific research, it can promote the development of big data research ideas and methods of online and offline integration. Through the establishment of intelligent medical platform, online data collection, data sorting, statistics and analysis are realized, and the feasibility is verified, which is combined with offline clinical practice. At the same time, we can also use artificial intelligence and big data technology to develop a variety of scientific research knowledge bases to guide clinical technology updates. Driven by big data, clinical research can eventually feed clinical diagnosis and treatment.

6.3 Promotion of international medical cooperation and building a human health community

With the continuous breakthrough of new technologies such as big data, artificial intelligence, and 5G, new products, new models and new business formats emerge one after another. Grasping the fourth industrial revolution characterized by networking, intelligence, and digitization, accelerating digital transformation, and building a new economic form are the focus of national development and the focus of international cooperation. After the outbreak of COVID-19, cooperation among countries has faced a series of challenges and is facing some new opportunities: Public health cooperation is advancing continuously; new ways and mechanisms of cooperation are constantly innovated; online economy and Internet economy have developed rapidly. For example, the (BRICs economic partnership strategy 2025) includes new themes such as "barrier-free and sanctions free trade and investment" and "digital economy benefits the people", which requires BRICs countries to strengthen cooperation in the process of digital transformation and eliminate the digital divide. In addition, according to the BRICs scientific and technological innovation framework plan, during Russia's presidency of the BRICs, more than 20 scientific and technological innovation activities related to the health field will be held, involving vaccine research and development intelligent medicine, etc. China and India are indispensable participants, contributors, and leaders in global health cooperation and important driving forces to boost BRICs cooperation. In this context, it is of great significance for Chinese enterprises to build an international intelligent medical cooperation platform by using new technologies such as the Internet of things, artificial intelligence, and big data. New technology is an important means to solve the supply shortage of medical service, uneven distribution of medical resources, and cumbersome cross-border medical procedures. It is an important channel for realizing the complementarity of medical resources and technical advantages. Therefore, enterprises, governments, and academia should join hands to vigorously develop new technologies such as artificial intelligence, the Internet of things and big data, and build a multi-level and multi-form international cooperation and exchange mechanism for hospital quality management, medical system construction, and smart hospital service on this basis. This will undoubtedly help to realize the cross-border cooperation of smart medicine and the sharing of cross-border medical resources so that patients can easily enjoy wider and pluralistic medical services. Furthermore, this will help build the "BRICs health community" and take the lead in building a human health community.

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