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Review

Artificial Intelligence Applications in Smart Healthcare: A Survey

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Abstract: The rapid development of AI technology in recent years has led to its widespread use in daily life, where it plays an increasingly important role. In healthcare, AI has been integrated into the field to develop the new domain of smart healthcare. In smart healthcare, opportunities and challenges coexist. This article provides a comprehensive overview of past developments and recent progress in this area. First, we summarize the definition and characteristics of smart healthcare. Second, we explore the opportunities that AI technology brings to the smart healthcare field from a macro perspective. Third, we categorize specific AI applications in smart healthcare into ten domains and discuss their technological foundations individually. Finally, we identify ten key challenges these applications face and discuss the existing solutions for each.

Keywords: artificial intelligence; smart healthcare; real-world application

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1. Introduction

In this age of information, massive amounts of data are continuously generated across various fields. Concurrently hardware technology has made it possible to process these data and derive valuable insights, which has fueled the rapid development of AI across numerous domains. Particularly in the healthcare field, people's pursuit of high-quality and efficient healthcare, along with the pressure on healthcare resources due to the growing population, has spurred the widespread integration of AI into healthcare. This integration has resulted in applications such as disease prediction and prevention, diagnostic imaging, and personalized treatment plans. The field encompassing these applications is smart healthcare, which originated from the concept of 'Smart Planet' proposed by IBM (Armonk, NY, USA) in 2009 [1]. Behind various types of AI applications in this field lies a common essential idea: after data are collected, ML (DL) techniques interpret them and present predictive analytics [2].

Smart healthcare differs from traditional healthcare because traditional healthcare follows a specialist-centered approach, while smart healthcare adopts a patient-centered approach by integrating AI technology [3]. In this approach, patients' needs, experience, and engagement are placed at the core of medical services through the incorporation of modern and intelligent healthcare solutions, thereby building a smart healthcare system.

There are several successful commercial implementations of smart healthcare. Merative L.P. provides smart healthcare products and services to nine of the top ten US hospitals [4]. Tempus collaborates with over 50% of all academic medical centers in the US [5]. Aidoc analyzes 2 million patients each month [6]. PathAI is utilized by 90% of the top 15 BioPharma companies to transform pathology [7]. Consequently, much research has focused on the applications and challenges of smart healthcare. Some research concludes that the future of smart healthcare is bleak due to the challenges of transforming data into wisdom [8]. In contrast, other researchers believe that smart healthcare could help solve challenges such as the shortage of medical personnel, aging populations, and high healthcare costs, while also facilitating sustainable development [9].

The opportunities that AI offers to the smart healthcare field are threefold: (1) predictive healthcare modeling, which involves processing and analyzing data at scale, recognizing patterns, detecting anomalies, making dynamic predictions, and supporting decision making; (2) discovering knowledge from structured and unstructured data, and achieving adaptive learning and continuous improvement; (3) providing cross-domain insights, facilitating research and innovation, and enhancing resource utilization [10].

Although the concept of smart healthcare is relatively new, there have been numerous real-world AI applications in this field, ranging from disease prediction and prevention [11] to drug discovery and development [12], and robotic surgery [13]. We categorize real-world AI applications in the smart healthcare field into ten domains, as outlined in several papers. For each domain, we introduce the specific AI technologies used and summarize the advantages of these technologies.

There are several challenges faced by AI applications in the smart healthcare field. Existing research analyzes the obstacles and shortcomings in each of the application domains [14]. In our review, we classify the challenges identified in these papers into ten categories and discuss each challenge and its existing solutions separately. Some of the challenges are common across several application domains, so research findings on these challenges will benefit all of them.

The rest of this article is organized as follows. Section 2 summarizes the definition and characteristics of smart healthcare. Section 3 examines the opportunities presented by AI in smart healthcare. Section 4 categorizes smart healthcare applications into different domains. Section 5 classifies the challenges faced by smart healthcare. Section 6 concludes the article.

2. Definition and Characteristics

2.1. Definition

There is no formal definition for AI applications in smart healthcare, but several sources provide summaries of AI in healthcare from their perspective, and we will present some of the commonly accepted definitions. Some believe it is the use of AI-enabled tools like ML, DL, and NLP to assist in and ideally improve the patient experience [15]. Others believe it is the use of machines to analyze and act on medical data, usually to predict a particular outcome [16]. According to Wikipedia, it is the use of AI to mimic human cognition in the analysis, presentation, and understanding of complex medical and healthcare data, or to exceed human capabilities by providing new methods for diagnosing, treating, or preventing diseases, exceeding human capabilities [17]. The American Medical Association defines the role of AI in healthcare as 'augmented intelligence', stating that AI will be designed and used to enhance human intelligence rather than replace it [18]. Some believe it is the use of AI tools to enhance, extend, and expand human capabilities, delivering the necessary types of care to patients when and where they need it [19].

2.2. Characteristics

AI applications in smart healthcare exhibit several characteristics, which can be summarized as the following three.

(1) Big data processing and analyzing. There are several types of healthcare data, such as EHRs, image data (including X-rays), audio data (like heart and lung auscultation), and video data (such as physiological monitoring videos). These data types can be classified into two categories, structured data and unstructured data, depending on whether the information has a set data model or has not been organized in a predefined way [20]. The applications employ AI models to process and analyze these data to make optimal

predictions and achieve continuous learning, and adaptability based on the continuous influx of new data.

(2) Augmented intelligence. In the smart healthcare field, the prevailing view is that AI should collaborate with human intelligence. This collaboration could include making the delivery of accurate results easier and faster, thereby assisting doctors in decision making; aiding nurses in managing vast quantities of patient data; and advising and guiding physicians on administering proper treatment; among other benefits [21]. However, in cases where machines surpass human performance, where errors do not result in severe consequences, or in situations where doctors are unavailable and machines can perform effectively, full AI automation is possible [19].

(3) Software and hardware combined. AI applications in smart healthcare encompass not only software components such as ML, DL, and NLP, but also hardware components like medical imaging equipment, vital signs monitoring equipment, and surgical robots. These applications can be classified into two categories: the first category analyzes structured data, attempts to cluster patients' traits, and infers the probability of disease outcomes; the second category extracts information from unstructured data, converts it into machine-readable structured data, and enables analysis by the first category applications [22].

AI applications in smart healthcare typically consist of several components. In this section, we describe their common architecture and functionality.

(1) Data collection and integration part

In the smart healthcare field, hardware such as medical imaging equipment, vital sign monitoring equipment, and wearable devices, is combined with software like data management systems and data integration systems to collect and integrate patients' EHRs, medical imaging, physiological data, and more [23].

(2) Unstructured data processing part

Approximately 80% of the data are unstructured and underutilized, including doctors' notes, medical images, and other audio and video recordings. To utilize these data, AI technologies such as ML, DL, NLP, or radionics, are employed to mine data, create or identify patterns in unstructured data, and extract structured data from these unstructured sources [24].

(3) Data preprocessing part

Data preprocessing in the smart healthcare field involves preparing medical data such as medical images, medical text, and vital signs monitoring data. This includes operations such as filling in missing data, normalization, and removing noise and outliers from the original data. These steps improve model performance, ensure data consistency, and prepare the data for use by AI algorithms [25,26].

(4) Algorithm and model part

Several AI algorithms are widely used in the smart healthcare field for tasks such as spotting DNA mutations in tumors, predicting heart attacks, and assessing suicide risk. AI models such as CNNs, which are highly promising for medical image recognition [27]; RNNs (including LSTMs), suitable for handling time-series data such as electrocardiograms and medical notes [28]; and SVMs, preferred for their simplicity, explainability, and effectiveness in areas like disease prediction and medical diagnosis [29], are commonly employed.

(5) Prediction analysis part

The prediction analytics component in smart healthcare performs advanced data analysis on health data to identify useful patterns and trends. These insights help medical professionals accurately predict future health events and outcomes. The prediction analytics component frequently aids in managing chronic diseases, early detection of high-risk patients, and predicting disease outbreaks [30].

(6) Decision support part

The decision support component in smart healthcare AI applications serves an advisory or watchdog role to reduce medical errors, including patient errors. This component falls into two main classes: the ML-based class, which relies on statistical inferences; and the ES-based class, which utilizes sophisticated rule-management subsystems within EHR systems [31].

(7) Feedback and optimization part

The feedback and optimization component is crucial for enabling AI applications in smart healthcare to learn, improve efficiency, and enhance accuracy continuously. This involves monitoring real-time performance, incorporating user feedback after each operation, and utilizing this feedback for optimization algorithms to refine the application's parameters [32].

Figure 1 depicts a common architecture of AI applications in the smart healthcare field. In this architecture, the data collection and integration component gathers data from various sources and integrates them into a unified dataset. If the dataset consists of unstructured data, it is sent to the unstructured data processing component, where it is transformed into structured data before moving to the data preprocessing component. If the dataset is already structured data, it goes directly to the data preprocessing component. In the data preprocessing component, the dataset undergoes cleaning, transformation, and processing to enhance its quality, accuracy, and availability. Subsequently, it serves as the input for the algorithm and model component.

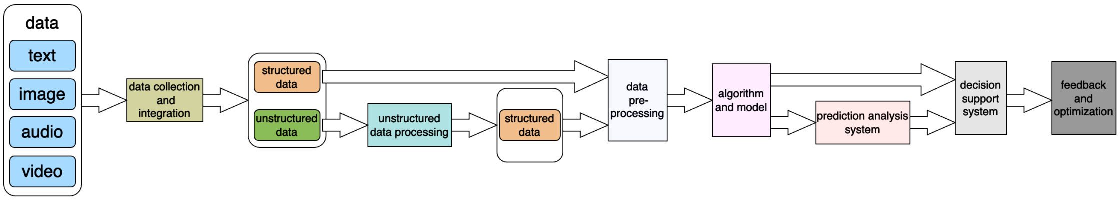

Figure 1. The overview workflow of artificial intelligent applications in the smart healthcare field.

The algorithm and model components employ specific AI algorithms and models on various input datasets for practical applications. The output either proceeds directly to the decision support component to provide evidence and support users in making informed decisions, or it first moves to the prediction analysis component to generate predictions of future events or outcomes. These predictions are then forwarded to the decision support component to aid users in making decisions. After processing through the decision support and prediction analysis components, the feedback and optimization component receives their results. It conducts a comprehensive evaluation of previous processes, assessing efficiency and accuracy, calculating parameters to enhance algorithms and models, and subsequently, updating these parameters.

3. Opportunities

In this section, we explore the opportunities that AI applications present to the smart healthcare field.

(1) AI plays a pivotal role in predictive healthcare modeling by processing vast amounts of data, including EHRs, medical imaging scans, and genetic information. Using advanced ML techniques such as DL and NLP, AI algorithms can identify complex patterns and subtle anomalies that may indicate potential health issues. They can also uncover hidden correlations and nonlinear relationships across diverse data sources, enabling more accurate predictions and personalized insights [33]. This capability enables dynamic prediction of various outcomes, such as disease progression and patient readmission rates, thereby supporting informed decision making for healthcare professionals. By continually learning from new data, AI-driven predictive modeling provides personalized insights

and treatment recommendations, ultimately enhancing patient outcomes and operational efficiency within healthcare organizations [34].

(2) AI facilitates knowledge discovery from both structured and unstructured healthcare data [35]. For example, ML and DL algorithms can extract structured information from unstructured data such as images, audio, and videos containing medical information. NLP algorithms can derive valuable insights from clinical notes, research articles, and patient feedback. Additionally, these AI algorithms can glean useful information from structured data such as EHRs. By analyzing these diverse data, AI systems gain a comprehensive perspective, expand the boundaries of knowledge, and adapt to new scenarios and challenges, enabling adaptive learning and continuous improvement [36]. For example, AI-powered diagnostic tools can learn from previous cases to enhance their accuracy over time, thereby improving diagnostic outcomes and treatment recommendations.

(3) AI provides cross-domain insights that promote research and innovation in healthcare. For example, AI-powered data analytics platforms can integrate data from various sources, such as patient records, genetic data, and environmental factors, to identify correlations and trends that may not be apparent to human analysts. This interdisciplinary approach enables researchers to gain deeper insights into disease mechanisms, treatment effectiveness, and public health trends. Moreover, AI-driven tools streamline workflows and enhance resource utilization, enabling healthcare organizations to allocate resources more efficiently and deliver better care to patients [37]. Overall, AI holds immense promise for transforming the smart healthcare landscape by unlocking valuable insights, improving decision making, and driving innovation across the healthcare ecosystem.

4. Applications

In the smart healthcare field, numerous real-world AI applications have been proposed in the recent literature. We categorize these applications into ten domains. The following sections survey these application domains in detail.

4.1. Disease Prediction and Prevention

AI applications in smart healthcare play a crucial role in predicting and preventing diseases such as COVID-19, liver disease, and cancer, utilizing SVMs as an ML method and CNNs as a DL method [38]. These AI algorithms analyze EHRs and patient lifestyle data, assisting physicians in interpreting medical images such as X-rays, magnetic resonance imaging, and computed tomography scans [39]. This capability enables more efficient and accurate disease prediction, thereby facilitating effective disease prevention.

For instance, during the COVID-19 pandemic, AI models were developed to predict outbreak hotspots by analyzing data from various sources, including social media, travel patterns, and healthcare reports. These models helped in early intervention and resource allocation, significantly impacting the management of the pandemic [40]. In liver disease prediction, AI models have been employed to analyze biomarkers and imaging data to identify early signs of liver fibrosis and cirrhosis. These models have shown higher accuracy compared to traditional diagnostic methods, enabling early treatment and better patient outcomes [41]. Similarly, in cancer detection, CNNs have been used to analyze mammograms and histopathological images, improving the accuracy of breast cancer diagnosis. AI algorithms have also been developed to predict the likelihood of cancer recurrence by analyzing patient data, which helps in tailoring personalized treatment plans and follow-up schedules [42].

However, doctors cannot entirely rely on these applications due to certain obstacles. In the future, efforts should focus on fostering a mutually beneficial relationship between AI and clinicians [43].

4.2. Diagnostic Imaging

In America, X-ray exams represent 60 percent of all imaging exams, and over 80 percent of health system visits include an imaging exam, placing significant pressure on healthcare providers. AI applications in diagnostic imaging not only generate results more efficiently but also more accurately by identifying problem areas or details that may be missed by the human eye. Current commercial clinical applications include general radiography, computed tomography, magnetic resonance imaging, fluoroscopy, and radiation therapy [44].

For example, in lung cancer screening, AI systems are used to analyze chest CT scans, assisting doctors by automatically detecting small nodules. Studies have shown that these systems can identify potential cancerous lesions earlier and more accurately than traditional methods, thus improving the success rate of early treatment [45]. In brain imaging, AI algorithms are employed to analyze MRI images to detect and monitor the progression of neurodegenerative diseases such as Alzheimer's. These algorithms can quantify changes in different brain regions, providing clinicians with detailed information to create personalized treatment plans [46]. Additionally, in fracture detection, AI systems have been used to analyze X-rays in emergency rooms, automatically identifying subtle fractures that may be overlooked by rushed physicians. One study found that these AI systems have accuracy comparable to experienced radiologists, helping to improve the diagnostic efficiency and accuracy in emergency settings [47].

AI applications play a pivotal role in image segmentation, computer-aided diagnosis, predictive analytics, and workflow optimization [48]. Moving forward, greater emphasis should be placed on the data-driven nature of this application. In addition to high-quality datasets, efforts should focus on generating more data and improving data quality [49].

4.3. Personalized Treatment Plans

Personalized treatment plans, also known as precision medicine, are defined by the National Institutes of Health as 'an emerging strategy for the prevention and treatment of disease that takes into account individual differences in genes, environment, and lifestyle for each person' [50]. The objective is to utilize individual biology rather than population biology at all stages of a patient's medical journey to enhance treatment effectiveness, reduce side effects, and prevent over-treatment [27]. AI applications can assist in personalized treatment plans by analyzing a patient's genomic data to identify genetic variations linked to specific diseases or treatment responses. For example, in oncology, AI can analyze the genomic profile of a tumor to identify mutations that may respond to specific targeted therapies. This allows oncologists to tailor treatment plans to the genetic makeup of the tumor, thereby increasing the likelihood of treatment success and minimizing side effects [51]. They can also analyze patient health data to uncover related patterns and associations, thereby developing personalized treatment plans based on patient preferences and values [52]. For instance, in diabetes management, AI can integrate data from continuous glucose monitors, dietary logs, and physical activity trackers to create personalized insulin dosing recommendations. This helps patients manage their blood sugar levels more effectively, reducing the risk of complications and improving their quality of life [53].

Given that personalized treatment plans involve sensitive, user-specific information, ensuring data security and user privacy is paramount [54]. Techniques such as federated learning and differential privacy can be employed to protect patient data while still enabling the development of accurate and effective personalized treatment plans. Federated learning allows AI models to be trained across multiple decentralized devices or servers without sharing raw data, while differential privacy ensures that any data used in AI training cannot be traced back to an individual patient [55].

4.4. Virtual Health Assistant

The virtual health assistant is an online platform designed to streamline disease identification for users by providing access to a centralized clinical database in an interactive format [56]. Leveraging NLP technology, it efficiently handles large volumes of user-generated natural language data, including text and audio [57]. For pattern recognition and classification problems, the SVM classifier performs best, and XGBoost is used for feature extraction to develop new feature combinations for training the SVM model [58].

The assistant engages intuitively with users through interfaces, responding to queries, sharing health information, and offering self-care recommendations [59]. It is not merely an information provider but a comprehensive health management tool. For example, users can input symptoms via voice or text, and the virtual assistant will use NLP technology to parse these inputs and retrieve relevant information from the clinical database. It then employs the optimized SVM model to identify possible diseases and provide suggested diagnostic results and care measures [60]. Additionally, the virtual health assistant shows great potential in managing chronic diseases. For instance, for diabetic patients, it can track blood glucose levels, diet, and physical activity, offering personalized advice to optimize health management. By integrating with wearable devices like smartwatches and glucose monitors, the virtual health assistant can receive real-time health data from users, providing dynamic feedback and recommendations. Real-time interaction and continuous monitoring help to improve patient adherence to treatment and overall health outcomes [61]. The virtual health assistant also plays a crucial role in mental health support. For users with anxiety or depression symptoms, the virtual assistant can guide cognitive behavioral therapy (CBT) techniques to help manage their emotional state. By analyzing users' emotions and behavior patterns, the virtual assistant can offer tailored advice to help users develop healthier psychological habits [62].

4.5. Remote Patient Monitoring

Remote patient monitoring Figure 2 involves tracking a patient's vital signs via wearable devices and remote monitoring tools, and alerting healthcare providers to any concerning changes [63]. This is particularly beneficial for patients requiring continuous monitoring, such as those unable to care for themselves in a healthy state or needing constant observation due to health or age-related concerns [64].

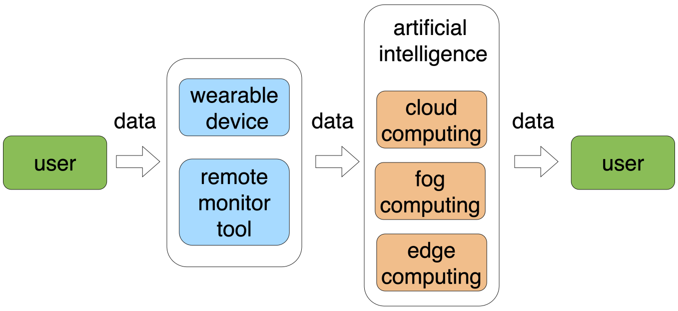

Figure 2. The overview of remote patient monitoring.

One notable example is the use of smartwatches and fitness trackers to monitor heart rate, blood pressure, and oxygen saturation in real time. These devices collect data continuously and send alerts to healthcare providers if they detect any abnormal patterns, such as irregular heartbeats or sudden drops in oxygen levels. This allows for timely intervention, potentially preventing severe health complications [65]. Another example is the use of continuous glucose monitors (CGMs) for diabetic patients. CGMs track blood glucose levels throughout the day and night, providing real-time data that can be shared with healthcare providers. This continuous monitoring helps in adjusting medication and dietary plans more accurately, improving overall diabetes management [53]. Additionally, remote patient monitoring systems can integrate with home-based devices like digital scales and blood pressure monitors. These devices automatically record and transmit data to a centralized system, where AI algorithms analyze the data for trends and anomalies. For instance, in patients with heart failure, sudden weight gain might indicate fluid retention, prompting an immediate review by healthcare providers [66].

They integrate DL to analyze data collected from devices and tools, and NLP to analyze patient feedback and electronic medical records [67]. Implementing remote patient monitoring requires not only the aforementioned AI technologies but also cloud computing for storing and sharing collected data and analyzing trends, fog computing and edge computing to bring cloud services closer to data collection devices, and blockchain technology to ensure the security and privacy of the entire system [65].

4.6. Drug Discovery and Development

In the field of drug discovery and development, AI has made significant contributions, including target identification, virtual screening, structure-activity relationship modeling, de novo drug design, optimization of drug candidates, drug repurposing, and toxicity prediction [68]. Two common AI techniques are employed: supervised learning (e.g., classification and regression) and unsupervised learning (e.g., clustering and dimensionality reduction). Supervised learning uses labeled data to train models for classifying or predicting outcomes, while unsupervised learning identifies recurring patterns and clusters unlabeled data without prior knowledge [69].

A specific example is the application of AI in anticancer drug discovery. Through machine learning algorithms, researchers can identify gene mutations associated with specific types of cancer from large amounts of genomic data. Subsequently, this information is used to virtually screen compound libraries to find compounds that are most likely to bind to these mutated genes and inhibit their function. This approach significantly shortens the time for drug discovery and increases the success rate [70]. In toxicity prediction, AI can predict the potential toxicity of new drugs by analyzing chemical structures and biological activity data. For instance, using supervised learning models, researchers can predict the toxicity of candidate drugs on the liver or kidneys, thereby excluding unsafe drugs in the early screening stages and reducing the risk of clinical trial failures [71]. Another example is the application of AI in optimizing drug compounds. Using AI-driven molecular generators, researchers can design new compounds that meet specific efficacy and safety requirements. This process involves using deep learning techniques, such as generative adversarial networks (GANs), to generate molecular structures with high activity and low toxicity from scratch. This approach greatly accelerates the design and optimization process of new drugs [72]. During clinical trials, AI enhances the quality of trial design and patient selection by reducing population heterogeneity and implementing prognostic and predictive enrichment strategies. For example, AI algorithms can analyze electronic health records (EHRs) and genomic data to select the most suitable patients for trials, thereby increasing the success rate of the trials. Additionally, AI-supported wearable devices can monitor the health status of trial participants in real time, providing continuous data streams that help to understand the effects and safety of the drugs more comprehensively [73].

4.7. Robotic Surgery

Robotic surgery driven by AI utilizes various AI models, including classification and regression trees, SVMs in ML, ANNs, and CNNs in DL [74]. AI-driven robotics have revolutionized surgical procedures, enhancing precision and improving patient outcomes. In complex surgeries, AI-controlled robots improve surgeons' visualization, dexterity, and control, while their precise movements reduce invasiveness, complications, and recovery times [59]. A prime example is the Da Vinci Surgical System, which employs robotic arms controlled by surgeons using a console. The system utilizes AI to assist with intricate movements, providing a high-definition, 3D view of the surgical area. This capability is particularly valuable in urological surgeries, such as prostatectomies, where precision is crucial to avoid damage to surrounding tissues and nerves [75].

AI-driven robotic surgery systems can be categorized along an assistive-to-autonomous spectrum. Assistive systems enhance user capabilities by analyzing data, executing tasks under human supervision, or learning from professional demonstrations [76]. For instance, in orthopedic surgery, the MAKO system uses AI to create 3D models of a patient's anatomy and assist surgeons in performing precise joint replacements. The AI system provides real-time feedback, ensuring implants are placed accurately, which improves patient outcomes and the longevity of the implants [77]. Autonomous systems respond to real-world conditions, make decisions, and operate with minimal or no human interaction [76]. An example of this is the Smart Tissue Autonomous Robot (STAR), which has demonstrated the ability to perform soft tissue surgeries, such as suturing, autonomously. STAR utilizes computer vision and AI algorithms to adjust its actions in real time based on the tissue's response, achieving consistent and precise results that are comparable to those of experienced surgeons [78].

While AI-driven robotic surgery systems with autonomous capabilities and independent robots represent the future, they are intended to supplement, rather than replace, surgeons in surgical care. For instance, during minimally invasive heart surgeries, AI-assisted robots can stabilize the surgeon's hand movements, filter out tremors, and enhance precision. However, the surgeon remains in control, making critical decisions and adjustments during the procedure [79].

4.8. NLP for Electronic Health Records

EHRs are vital in healthcare, storing patient clinical tests, records, and treatments, encompassing both structured (symptomatic codes, lab results) and unstructured data (clinician observations). NLP plays a crucial role in analyzing unstructured data and extracting meaningful information from it [50]. Several critical NLP tasks aim to render narrative, ambiguous, and highly unstructured language data comprehensible and analyzable for computers, such as morphological analysis, semantic analysis, named-entity recognition, and word-sense disambiguation [80]. Pre-trained language models extract representations to compute disease contributions, maximizing EHR data utilization and effectively leveraging healthcare domain knowledge [81].

In practice, NLP has been applied to various EHR-related tasks. For example, the MIMIC-III dataset has been widely used to train and evaluate NLP models that can automatically extract and classify symptoms and diagnostic information from medical records, thereby improving healthcare service efficiency. Specific applications include automatically identifying and tagging drug allergies in medical records using NLP, which enhances patient safety, and using named-entity recognition techniques to extract patients' medical history and surgical records from medical records, aiding physicians in diagnosis and treatment decisions [82].

However, excessive or inaccurate NLP outputs in EHRs may cause users to disregard its intelligence, reducing productivity. Therefore, healthcare NLP software should prioritize actionable insights with minimal noise for providers. Accurate predictions depend on the quality and completeness of training data, making data quality a critical concern. Additionally, protecting patient data security and privacy is crucial, and AI usage in EHRs must comply with laws such as HIPAA in the US [10].

4.9. Behavioral Health Support

AI effectively diagnoses mental illnesses using methods inaccessible to human therapists by accessing, integrating, and analyzing patient data from diverse sources [83]. Primary technologies include ML and DL for accurate diagnosis and outcome prediction in mental health, computer vision for analyzing imaging data and interpreting non-verbal cues such as facial expressions and gestures, and NLP for speech recognition, text analysis, and understanding clinical documentation. Behavioral health support data are sourced from sensors for monitoring, social media platforms, and multimodal devices like smartphones, wearables, and physiological sensors. This provides real-world, continuous data on symptoms, treatment responses, behaviors, thoughts, and emotions [84].

To elaborate further on AI's application in behavioral health support, several specific examples include emotion recognition and sentiment analysis, sleep monitoring and intervention, and digital therapy and intervention. AI can identify users' emotional states by analyzing text content in social media posts and messages, predicting tendencies towards depression or anxiety through tweets, and confirming emotional states via facial expression recognition in video calls or photos [85]. Using wearable devices like smartwatches, AI monitors sleep patterns, detects insomnia or other sleep disorders, and provides personalized recommendations, such as adjusting sleep schedules or performing relaxation exercises to improve sleep quality [86]. Additionally, AI-driven applications offer digital interventions like cognitive behavioral therapy (CBT) to help manage anxiety, depression, and other mental health issues. For instance, some applications use chatbots to interact with users, providing support and advice, simulating the role of a human therapist [87].

However, compared to human psychotherapists, AI can better monitor and predict human mental health but lacks understanding of human emotions and the ability to provide humanized care and support.

4.10. Clinical Trial Matching

Clinical trials recruit at-risk individuals to test experimental drugs, but limited sample sizes and the heterogeneity of diseases hinder precise assessments of disease severity and progression. To address this challenge, multimodal data from large cohort and population studies offer promising solutions [88]. Researchers can leverage technologies like ML and DL to automatically identify patterns in vast datasets. For example, ML algorithms can analyze patient data to predict eligibility for trials with high accuracy. Deep learning models might process imaging data and genomic information to identify patients who fit complex criteria for specific studies [89]. Additionally, NLP enables the understanding and correlation of evidence in spoken or written language [90]. For instance, NLP can analyze clinical notes and trial descriptions to ensure that patient information aligns with trial requirements. This capability is exemplified by systems that automate eligibility surveillance, linking trial descriptions with clinical data in electronic health records (EHRs) to identify eligible patients accurately [91].

One effective solution is automating clinical trial eligibility surveillance to address oversights in patient eligibility. An automated system utilizes NLP and ML/DL algorithms to detect eligible patients by linking trial descriptions to clinical data in EHRs [92]. For instance, systems like IBM Watson for Clinical Trial Matching use NLP to parse and interpret trial protocols and patient records, matching individuals to appropriate trials based on complex criteria [93]. Furthermore, Bayesian nonparametric models (BNMs) offer a flexible, nonparametric approach that allows for the utilization of infinite-dimensional parameter sets with a finite subset of limited parameters, streamlining the clustering process and reducing trial design time [73].

5. Challenges and Existing Solutions

5.1. Data Integration and Interoperability

5.1.1. Challenges

In the smart healthcare field, data heterogeneity is a common challenge that hinders the application of AI, complicating the integration and interoperability of various data sources. Data heterogeneity refers to differences in data structures, formats, or semantics across different sources or systems, such as different departments within the same medical institution, different institutions within the same medical system, or even different medical systems. Additionally, data heterogeneity includes diverse data types, structures, and standards within the same data sources or systems, such as differences between structured, semi-structured, and unstructured data, as well as variations between text, images, audio, and video data [24] Figure 3.

To explore this issue in detail, several aspects can be considered: within the same medical institution, different departments may use varying data formats and standards, increasing the complexity of data integration; within the same medical system, different institutions may have significant differences in data standards and formats, requiring complex mapping and conversion processes for interoperability; the difficulty of data integration between different medical systems is even greater, with differing standards and regulations between public and private medical systems creating more barriers; within the same system, the diversity of data types can also lead to heterogeneity issues, such as patient records containing text, lab test results, medical imaging, and audio recordings, each requiring different processing and analysis methods; even within the same type of data, different systems may use different standards, such as different coding systems for the same disease, complicating data comparison and integration. A detailed examination of these aspects can help better understand the impact of data heterogeneity on AI applications and propose solutions such as adopting unified standards, developing cross-system data conversion tools, and using advanced machine learning algorithms [24].

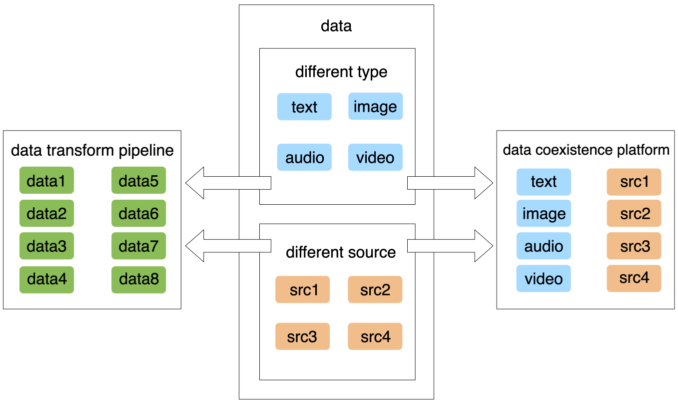

Figure 3. The overview of data heterogeneity.

5.1.2. Existing Solutions

Currently, several methods are available to achieve data integration and interoperability. For example, the Artificial Intelligence Modern Data Platform (AIMDP) integrates the core features of the modern data platform with data science capabilities to handle various data types. In practice, this platform can manage both structured data (e.g., electronic health records) and unstructured data (e.g., medical images). For instance, in a large healthcare institution, AIMDP can integrate data from different departments, such as laboratory results, patient monitoring data, and clinical notes. By utilizing its experimentation and knowledge extraction modules, the platform helps clinicians extract valuable insights from integrated data, thereby optimizing patient treatment plans [94]. The second method involves transforming available data into data with similar properties and structure. This can be achieved by developing a data harmonization pipeline that adheres to the common FHIR data standard. The process includes querying data from the hospital database, performing FHIR mapping, conducting syntactic validation, transferring harmonized data into a patient-model database, and exporting data in an AI-friendly format. For example, in diabetes management, a hospital can consolidate patient blood glucose data, weight, and dietary records from various sources into a unified FHIR standard. This ensures that the data can be consistently used across different medical applications, enhancing the personalization and accuracy of treatment [95]. The third method uses Health Level 7 FHIR as a health data content modeling and exchange standard. This involves extracting health data from various sources, converting them into a standardized FHIR format, and ensuring data consistency and interoperability. For example, in a cross-regional healthcare network, hospitals can share patient medical records using the FHIR standard, facilitating seamless information exchange. A specific instance is in cancer treatment, where genetic information, treatment history, and current clinical data can be integrated through FHIR standards, allowing specialists across different hospitals to access comprehensive patient information on a unified platform and devise the best treatment plans [96].

5.1.3. Evaluation of the Existing Solutions

The pros and cons of the three methods include, firstly, the Artificial Intelligence Modern Data Platform (AIMDP) offers comprehensive data management capabilities and can handle both structured and unstructured data, aiding in the extraction of valuable insights from integrated data. However, its complexity and high implementation costs could be drawbacks [94]. The second method involves developing a data harmonization pipeline that adheres to the FHIR data standard. Its advantages include ensuring data consistency and standardization, which facilitates interoperability between different systems and applications. However, it requires rigorous data validation and transformation processes, with a substantial initial workload [95]. The third method uses Health Level 7 FHIR as a health data content modeling and exchange standard. Its benefits include widespread adoption and support, promoting collaborative care and treatment planning. However, it demands significant effort to convert and maintain data in the FHIR format and ensure consistent implementation across different systems [97]. Overall, the choice of data integration and interoperability methods should be based on the specific needs and capabilities of the institution. Large institutions may find AIMDP most suitable, while those focused on standardization and interoperability may prefer data harmonization or FHIR standards.

5.2. Large-Scale Data Handling

5.2.1. Challenges

In the healthcare field, there has been an exponential surge in data volumes, fueled by advancements in medical technology, widespread EHR adoption, and the proliferation of wearable health devices. These diverse data streams originate from clinical systems, personal wearable devices, IoT devices, and open medical repositories [98]. This diversity includes clinical notes, imaging data, sensor readings, and genomic data, among others. The complexity and enormity of these datasets often surpass the capacity of conventional data management systems, hindering efficient storage, management, and processing [99]. For instance, a hospital's radiology department generates terabytes of imaging data annually, while EHR systems capture extensive patient history, treatment plans, and outcomes. Despite AI's enhanced data processing capabilities, its potential to drive meaningful insights and advancements in healthcare remains constrained without concurrent improvements in data infrastructure. To effectively harness AI, healthcare organizations must invest in scalable data platforms, employ advanced analytics, and ensure robust data governance frameworks to handle the data's volume, variety, and velocity.

5.2.2. Existing Solutions

Several papers discuss potential solutions to this problem. This paper summarizes five common big data handling mechanisms in the healthcare domain: ML mechanisms, agent-based mechanisms, heuristic and meta-heuristic-based mechanisms, cloud-based mechanisms, and hybrid mechanisms. Each offers high performance and scalability but may also present challenges, such as requiring significant training time and resources, being complex, lacking optimal solutions, raising privacy concerns, and lacking quality control and access to learning resources [99]. The first method involves using Hadoop to implement the MapReduce algorithm, which is well established for processing and generating large datasets. In healthcare, Hadoop has been effectively applied to analyze electronic health records (EHRs). For example, the Research Data Warehouse at the Mayo Clinic employs Hadoop to manage and analyze extensive datasets from clinical trials and patient records. By distributing computation across a cluster of machines, Hadoop's MapReduce facilitates the aggregation of patient data, complex queries, and statistical model generation. This method excels in environments where data are dispersed across multiple sources, enabling comprehensive analysis without requiring data centralization [100]. The second method utilizes Apache Spark, which provides in-memory processing through resilient distributed datasets (RDDs). This capability significantly accelerates data analysis compared to traditional disk-based methods. In genomic research, for instance, Spark's efficient execution of iterative algorithms has been pivotal. The Genomics England initiative illustrates Spark's application, where it analyzes whole-genome sequencing data to identify genetic variations associated with rare diseases. Spark's in-memory processing allows rapid analysis of large and complex datasets, such as those involving numerous genomic variants, thus speeding up discovery and improving diagnostic efficiency [101]. However, processing very large datasets may require substantial memory resources, making it important to compare Spark and Hadoop based on dataset size and computational needs [102]. The third method addresses the need for robust recognition models to handle the diverse, large-scale, and complex nature of healthcare data. Data mining techniques, such as clustering and classification algorithms, are employed to identify patterns and extract insights from extensive datasets. For example, the Diabetes Control and Complications Trial (DCCT) used data mining to predict the risk of complications based on historical patient data. Predictive models using data mining, such as decision trees and neural networks, analyze EHRs to forecast cardiovascular events and other health risks. These models help in developing targeted interventions and personalized treatment plans, thereby enhancing patient care and outcomes [103].

5.2.3. Evaluation of the Existing Solutions

Regarding the pros and cons of the three methods mentioned above. Firstly, Hadoop's MapReduce is highly effective in distributed data environments and large-scale batch processing, offering significant scalability and cost-effectiveness. However, it requires considerable setup and maintenance efforts, and its performance in real-time data processing may be limited [100]. Secondly, Apache Spark provides fast analysis through in-memory processing, which is particularly beneficial for iterative algorithms, but it requires substantial memory resources, which can be expensive and challenging to manage for extremely large datasets [101]. Thirdly, data mining techniques offer valuable insights through pattern recognition and predictive modeling, aiding personalized care and risk prediction. However, these methods require high-quality, well-labeled datasets and may face challenges with data heterogeneity and model interpretability [104]. Overall, Hadoop is more suitable for large-scale, distributed data processing, while Spark is ideal for high-speed, iterative analysis. Data mining techniques are crucial for extracting actionable insights and developing predictive models to improve patient outcomes.

In addressing the challenges of large-scale data handling, it is essential to consider the comparative performance of existing frameworks like Hadoop and Spark. Based on the experimental results from multiple studies, it has been consistently demonstrated that Spark outperforms Hadoop in various scenarios, particularly in terms of execution speed and efficiency. For instance, one study conducted in a controlled laboratory environment compared Hadoop and Spark using WordCount and TeraSort workloads, revealing that Spark achieves up to two times speedup in WordCount and up to 14 times in TeraSort when parameters are appropriately tuned [105]. Another comprehensive evaluation highlighted that Spark's in-memory processing allows it to significantly outpace Hadoop's disk-based MapReduce, resulting in much faster query execution. Additionally, Spark's versatility, with built-in modules for stream processing, machine learning, and graph processing, further solidifies its superiority for complex applications [106]. However, it is important to note that Hadoop-MapReduce remains more suitable and cost-effective for truly massive batch processing tasks, reflecting the necessity of selecting the right tool based on the specific data handling requirements. These comparative analyses underscore the importance of choosing frameworks that align with the nature of the workload, thereby optimizing resource utilization, execution time, and overall efficiency [107].

5.3. Real-Time Processing

5.3.1. Challenges

In the realm of smart healthcare, the burgeoning Internet of Things (IoT) has led to an explosion of data that demand immediate processing to derive actionable insights. Traditional data analysis methods, which rely on centralized servers, often introduce latency that undermines the effectiveness of real-time applications Figure 4. This limitation has exposed the insufficiency of cloud computing alone in meeting the diverse and dynamic data analysis requirements of modern intelligent systems. As a solution, fog and edge computing have emerged as pivotal technologies. By decentralizing data processing and relocating computational resources closer to the data source, these approaches significantly reduce latency and enhance processing efficiency. For instance, edge computing allows for real-time analytics directly at the point of data generation, such as wearable health monitors analyzing patient vitals on the device itself. This minimizes the delay inherent in transmitting data to and from the cloud, facilitating quicker responses and more timely insights. Similarly, fog computing extends this capability by providing additional storage and computational power at intermediate nodes between the edge and the cloud. This model can handle more extensive data processing tasks, such as aggregating and analyzing health data from multiple sources within a smart hospital network, while still addressing the latency issues associated with cloud-based solutions [108].

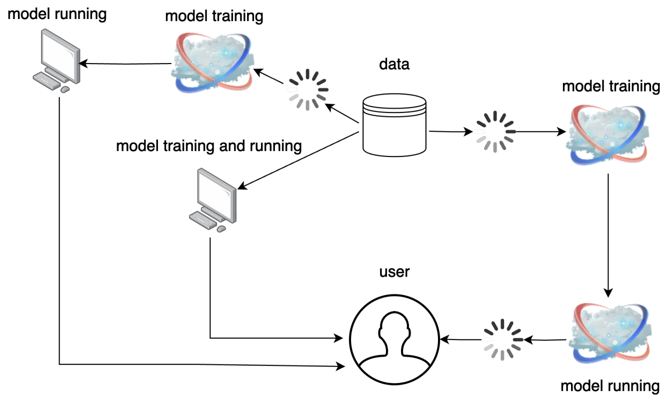

Figure 4. The overview of real-time processing.

5.3.2. Existing Solutions

Regarding edge computing, there are two practical approaches. The first involves performing AI reasoning tasks on the edge while conducting AI training tasks in the cloud. The second approach is to perform part or all of the AI training and reasoning tasks at the edge [109]. Integrating edge computing with artificial intelligence enables efficient gathering, storage, and processing of IoT data, facilitating rapid real-time analysis and decision making. This synergy empowers decentralized, low-latency, and reliable application services [110]. Although edge computing already significantly reduces latency, some models can further optimize it. For example, Smart-Edge-CoCaCo is proposed to minimize latency by jointly optimizing the wireless communication model, the collaborative filter caching model, and the computing offloading model [109]. In practical applications, Smart-Edge-CoCaCo can be used in smart city traffic management systems, where it analyzes traffic data in real time to optimize traffic signals, thus reducing congestion and improving traffic flow efficiency. Regarding fog computing, while its transmission delay may be higher than that of edge computing, its storage and computing capacities are superior [111]. Existing fog models have limitations, often prioritizing either precision or faster response times, but not both. Some research projects propose architectures to address this problem, such as integrating quartet DL with edge computing devices [112]. For instance, in intelligent medical monitoring systems, quartet deep learning models can process large volumes of physiological data, such as heart rate and blood pressure, at the fog computing layer, providing accurate health monitoring and early warning while ensuring quick response times.

5.3.3. Evaluation of the Existing Solutions

Regarding the pros and cons of the two approaches mentioned, firstly, edge computing combined with artificial intelligence can effectively collect, store, and process IoT data, providing rapid real-time analysis and decision making, reducing latency, and improving the reliability of application services. For example, Smart-Edge-CoCaCo can further reduce latency by optimizing the wireless communication model, collaborative filter caching model, and computing offloading model. However, edge computing may face resource limitations when handling complex tasks and large-scale data [109]. Secondly, fog computing, although having higher transmission latency, offers superior storage and computing capacities. For instance, in intelligent medical monitoring systems, quartet deep learning models can process large volumes of physiological data at the fog computing layer, providing accurate health monitoring and early warning while ensuring quick response times. However, existing fog computing models often struggle to balance precision and response times [113]. In conclusion, edge computing is suitable for scenarios requiring low latency and high reliability, while fog computing is better suited for tasks involving complex computations and large-scale data. By considering the actual conditions and performance requirements of the application, the optimal system design can be achieved.

5.4. Model Interpretability

5.4.1. Challenges

In the healthcare domain, the opacity of AI applications during decision-making processes is a significant concern. Although AI technologies such as machine learning (ML) and deep learning (DL) possess powerful capabilities, they often fail to explain their predictions, making their decision-making processes appear as "black boxes" that are difficult to interpret. This lack of transparency can lead to distrust among healthcare professionals and patients regarding AI decisions. For instance, an AI system might provide a diagnostic result without a clear explanation supporting it, making it challenging for doctors to verify or understand the basis of the AI's judgment. Consequently, healthcare professionals continue to rely on evidence-based diagnoses, and patients struggle to build trusting relationships with their providers. Therefore, it is essential to develop more interpretable AI models to address the opacity in AI decision making, such as by explaining the rationale behind model decisions and the importance of features, thereby enhancing the transparency and trustworthiness of decisions [114].

5.4.2. Existing Solutions

XAI sheds light on the opacity of black-box models by unveiling crucial insights such as feature importance and correlations. By elucidating the decision-making process, users gain transparency into how, why, and when decisions are made. This empowerment allows users to evaluate both outcomes and input factors, thereby enhancing decision making. XAI techniques strike a balance between explainability and high accuracy, even in intricate models [115]. Commonly used XAI methods in practice include LIME, SHAP, Grad-CAM, and t-SNE. For instance, LIME (Local Interpretable Model-Agnostic Explanations) provides local approximations of the model's predictions, helping users understand which features most influenced a specific decision. SHAP (Shapley Additive Explanations) assigns an importance value to each feature, offering a clear view of feature contribution across the model. Grad-CAM (Gradient-Weighted Class Activation Mapping) highlights the regions of an image that the model focuses on when making a prediction, which is particularly useful in medical imaging for identifying areas of concern. t-SNE (t-Distributed Stochastic Neighbor Embedding) is a dimensionality reduction technique that helps visualize high-dimensional data, making it easier to identify patterns and clusters. In the medical field, visual descriptions are the most utilized explanation method, followed by numerical and rule-based descriptions. For example, in diagnosing diabetic retinopathy, Grad-CAM can be used to show which parts of an eye image were most influential in the diagnosis, thereby assisting doctors in validating the AI's findings. Another example is using SHAP values to interpret a predictive model for patient readmissions, allowing healthcare providers to understand which factors (e.g., age, previous hospital visits, specific health conditions) are most critical. Evaluation criteria for XAI methods typically focus on usability and reliability, assessing how user-friendly and accurate these methods are in providing explanations for their predictions [116]. Sometimes, the interpretability and explainability of AI algorithms can be misunderstood, affecting how we evaluate and implement them. Interpretability involves understanding the inner workings of a system and predicting outcomes based on changes in input or parameters. In contrast, explainability focuses on providing clear justifications or reasoning for model decisions, helping users grasp the significance of system parameters [117].

5.4.3. Evaluation of the Existing Solutions

LIME helps users understand which features affect individual predictions, aiding in troubleshooting and model improvement. However, its focus on local approximations can miss broader patterns and may be sensitive to the choice of local models, potentially leading to inaccurate interpretations [118]. SHAP offers a detailed and consistent view of feature importance, improving model transparency. Nonetheless, it can be computationally expensive, especially for complex models and large datasets [119]. Grad-CAM is useful for visualizing relevant areas in medical imaging, highlighting influential regions of an image. However, it is limited to convolutional neural networks and does not provide a complete explanation of the decision process [120]. t-SNE helps in understanding data structure and relationships through visualization, but it can be computationally intensive and may distort global data structures, leading to potential misinterpretations [121]. In conclusion, LIME is suitable for local interpretability but may overlook global patterns, while SHAP provides a comprehensive view of feature importance at the expense of computational efficiency. Grad-CAM is effective in visual domains but model-specific, and t-SNE is beneficial for data visualization but may distort global data structures. Combining multiple XAI techniques can offer a more complete understanding of model behavior, addressing the limitations of individual methods and enhancing decision-making processes.

5.5. Continuous Learning and Adaptability

5.5.1. Challenges

In the healthcare sector, AI applications face challenges related to continuous learning and adaptability. Although AI systems can be initially trained on large datasets, maintaining long-term relevance and accuracy remains problematic due to the complexity and constant evolution of medical practices [122]. For instance, the emergence of COVID-19 highlighted the need for AI diagnostic tools to rapidly adapt to new SARS-CoV-2 variants and evolving treatment protocols. Similarly, the rapid development of targeted cancer immunotherapies, such as CAR-T cell therapies, requires AI models to be continuously updated to ensure they reflect the latest clinical evidence and therapeutic guidelines, preventing potential misdiagnoses. IBM Watson Health demonstrates the importance of ongoing model refinement by integrating real-time updates from the latest medical research and clinical trial results into its decision-support systems. Additionally, the adoption of advanced surgical techniques, such as robot-assisted minimally invasive surgeries, necessitates that AI models incorporate new procedural data and outcomes to provide current and relevant guidance [123]. These examples underscore the critical need for ongoing model optimization and updates in the healthcare environment to sustain the effectiveness and reliability of AI systems.

5.5.2. Existing Solutions

Continuous learning in AI involves adapting algorithms to continuously evolving data without a predefined number of tasks. In healthcare, this capability is vital due to the constant changes in patient data and clinical practices. For instance, IBM Watson for Oncology updates cancer treatment recommendations by integrating the latest medical research and patient data, quickly adapting to new immunotherapy advancements [124]. Similarly, Dexcom's glucose monitoring system adjusts insulin dosages in real time based on current blood glucose levels, optimizing diabetes management [125]. During the COVID-19 pandemic, AI systems like BlueDot refined predictive models and issued early outbreak warnings by analyzing real-time health data and news [126]. Tempus Labs uses AI to analyze genomic data, regularly updating its database with the latest genetic research to provide precise, personalized treatment recommendations. These examples highlight how continuous learning allows healthcare AI systems to stay up to date with evolving data and practices, enhancing the accuracy and effectiveness of medical services.

The primary challenge in continuous learning models is their susceptibility to catastrophic forgetting or interference, caused by fixed and limited storage allocation. This occurs when training a model with new information interferes with previously learned knowledge, often leading to a sudden decline in performance or complete replacement of old knowledge with new information [127]. In continuous learning, various approaches are employed to balance old and new tasks and mitigate forgetting and interference problems. Regularization-based methods add explicit terms to the loss function to achieve this, while replay-based methods approximate and recover old data distributions. Optimization-based approaches manipulate optimization procedures, such as gradient projection or meta-learning. Representation-based techniques leverage representations for continual learning, incorporating self-supervised learning and pre-training. Architecture-based strategies allocate task-specific parameters to alleviate inter-task interference, thereby enhancing model flexibility and adaptability [128]. In practice, when implementing continuous learning, considerations should extend beyond fixed and limited storage allocation to include computational costs. Various methods achieve this balance. For instance, using a k-NN classifier continuously updated alongside a fixed, pre-trained feature extractor is ideal for adapting to dynamic data streams within limited computational budgets, ensuring retention of previously seen data [129].

5.5.3. Evaluation of the Existing Solutions

Continuous learning allows AI systems to adapt to new data and evolving conditions without predefined tasks, which is crucial in dynamic fields like healthcare. However, this approach faces challenges such as catastrophic forgetting, where new information interferes with previously learned knowledge, potentially leading to performance degradation. To address this issue, various methods have been employed, including regularization-based techniques, replay-based methods, and architecture-based strategies. While these methods effectively balance new and old tasks, they often come with increased computational costs and complexity [130]. Overall, continuous learning offers significant advantages in keeping AI systems up-to-date and effective, but it requires careful management of learning dynamics and computational resources to mitigate risks like forgetting and to ensure sustainable performance.

5.6. Security of AI Models

5.6.1. Challenges

In the healthcare sector, AI models face significant security challenges throughout the stages of data collection, preprocessing, model training, and inference Figure 5. During data collection, there is a risk of sensor spoofing attacks, while preprocessing is susceptible to scaling attacks. The sensitive nature of medical data makes it a prime target for malicious activities. Additionally, AI models themselves may be vulnerable to adversarial attacks, which involve subtle modifications to input data that can lead to incorrect predictions or compromise patient privacy, often escaping human detection [131]. These security concerns highlight the need for robust security measures and protocols to protect patient information and ensure the integrity of AI-driven healthcare systems. For instance, protecting sensors from falsification and tampering is crucial during data collection, while ensuring that models have sufficient robustness against adversarial attacks is equally important during model training and inference. These measures contribute to enhancing the security and reliability of healthcare AI systems.

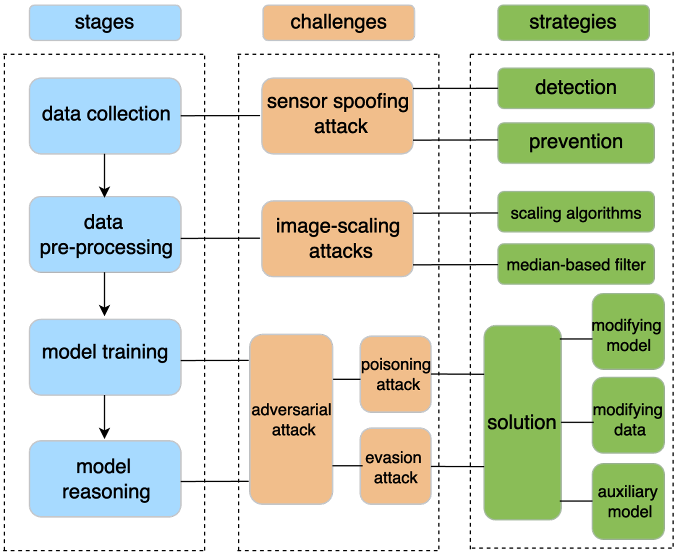

Figure 5. The overview of the security of AI models.

5.6.2. Existing Solutions

In the healthcare sector, effectively detecting and preventing sensor spoofing attacks is essential for maintaining data integrity. For instance, remote monitoring systems, such as heart rate monitors and glucose meters, must guard against data falsification. By integrating sensor data with electronic health records, healthcare systems can use anomaly detection algorithms to spot potential spoofed data. For example, machine learning models can track unusual fluctuations in heart rate data to identify and mitigate spoofing attempts, thus enhancing diagnostic accuracy [132]. Additionally, data fusion techniques play a critical role. For example, Dexcom's continuous glucose monitoring system merges real-time glucose levels with historical medical records and lab results to detect anomalies and prevent the influence of spoofed data on diabetes management decisions. Similarly, integrating various sensor data, like ECG and SpO2, with clinical data can improve the detection of spoofed data and boost the overall reliability of healthcare systems [132].

Addressing image scaling attacks is crucial in medical imaging for maintaining diagnostic accuracy. The choice of scaling algorithms significantly impacts image quality. Hospitals can use robust algorithms, such as area scaling, to ensure high-quality images during scaling. For example, in automated breast cancer image analysis, this approach helps recover manipulated data, ensuring accurate diagnoses [133]. Additionally, median filters are valuable for repairing damaged medical images. In scenarios where CT or MRI images are affected by scaling or compression, median filters can effectively remove noise and restore original image details. For instance, applying median filters to chest CT scans can correct artifacts caused by processing errors, ensuring accurate diagnostic information [133]. This method is widely utilized in image analysis software to enhance image quality and diagnostic precision.

In healthcare, defending against adversarial attacks, including poisoning and evasion attacks, is critical. Poisoning attacks may introduce malicious samples into training data, compromising model performance. Techniques such as adversarial retraining and input reconstruction can improve model resilience. For example, cleaning and re-labeling training data helps mitigate the impact of malicious samples [134]. For evasion attacks, generative adversarial networks (GANs) can bolster the security of predictive models. In breast cancer risk prediction, GANs generate adversarial examples to simulate potential attacks, enabling models to detect and counter malicious inputs. These examples enhance model robustness against real-world evasion attacks. Furthermore, GANs can also produce high-quality medical images to train models for recognizing various lesions, thereby improving their ability to withstand malicious inputs [134].

5.6.3. Evaluation of the Existing Solutions

To address security concerns in AI models within healthcare, each method has distinct advantages and limitations. Detecting and preventing sensor spoofing attacks through anomaly detection and data fusion ensures data integrity by identifying and mitigating falsified sensor data. However, these methods might struggle with high false positive rates and require integration with existing electronic health records, which can be complex [135]. Image scaling attacks can be managed with robust algorithms and median filters that improve image quality and diagnostic accuracy, though they may not fully restore original data and can add computational overhead [136]. For defending against adversarial attacks, techniques like adversarial retraining and generative adversarial networks (GANs) enhance model robustness against poisoning and evasion attacks, but they can be computationally expensive and require continuous updates to remain effective [137]. Overall, while each method contributes significantly to improving AI model security, its effectiveness can be influenced by implementation complexity, computational costs, and the need for ongoing adaptation. Combining these approaches, tailored to specific attack types and system requirements, offers a more comprehensive strategy to safeguard healthcare AI systems.

5.7. Ethical AI Design

5.7.1. Challenges

Since its inception, artificial intelligence has raised significant ethical issues, crucial for ensuring responsible and fair applications of the technology. One primary challenge is accountability: determining who is responsible for system failures when AI errors impact medical outcomes becomes complex. This challenge is exacerbated by the often opaque nature of AI decision-making processes, which makes it difficult to trace errors back to specific actions or decisions. Existing medical AIs cannot think and make decisions independently, and thus, cannot be considered duty bearers. Consequently, human responsibility must be assigned to various stakeholders such as doctors, AI developers, and others based on operational errors, faults within the AI itself, or negligence by related parties. The allocation of liability should be based on fault attribution or the principle of fairness [138]. Bias in AI systems often stems from poor design or the use of imbalanced or incomplete data. This can lead to discriminatory outcomes, perpetuating existing healthcare inequalities and failing to address the needs of certain patient groups fairly. Addressing AI bias is essential to avoid discriminatory practices and ensure that AI systems serve all patient groups equitably [139]. Data privacy is a major concern, particularly in healthcare AI applications. These systems frequently handle sensitive patient data, increasing the risk of privacy breaches and unauthorized access. Patients' privacy rights may be threatened, potentially leading to serious ethical and legal issues [140]. Overall, the existence of these ethical issues underscores the need for careful consideration in the development and application of AI technologies to ensure they are used responsibly and fairly.

5.7.2. Existing Solutions

To address accountability issues, clear frameworks for assigning responsibility in AI-driven healthcare systems need to be developed. This includes defining the roles and responsibilities of all stakeholders involved, such as developers, healthcare providers, and users. Developing comprehensive accountability guidelines can help in establishing who should be held responsible for errors or system failures, and mechanisms should be put in place to address such issues effectively [138].

Several strategies can be employed to mitigate AI biases. First, using diverse and representative datasets during AI development is crucial. For example, incorporating datasets with images from various skin types and demographics in diagnosing skin diseases helps prevent bias and improves accuracy. The MelanomaAI project demonstrates how diverse datasets enhance diagnostic performance and reduce disparities. Second, conducting regular audits to assess AI fairness, accuracy, and performance is essential [141]. Tools like IBM's AI Fairness 360 provide frameworks for evaluating AI models and addressing identified biases. Third, validating AI models across different patient populations and conditions is important for confirming their effectiveness. For instance, the HealthMap project shows how validating AI models in various regions and conditions maintains robustness and accuracy [142]. Lastly, educating clinicians and patients about inherent AI biases through training programs and workshops helps manage AI tools effectively and recognize potential biases.

Several strategies can be employed to effectively address AI biases, each with pros and cons. First, using diverse and representative datasets is crucial for reducing bias and improving accuracy, though this approach can be resource-intensive and it can be challenging to ensure comprehensiveness. Second, conducting regular audits helps identify and address biases, ensuring fairness; however, audits can be costly and require continuous updates to remain relevant. Third, validating AI models across different populations confirms their effectiveness in various scenarios, but this process can be complex and time-consuming. Finally, educating clinicians and patients about AI biases raises awareness and improves the management of AI tools, though it requires significant investment in training and education [143]. In conclusion, while each method contributes valuable insights for mitigating AI bias, it also presents challenges that need to be managed. Combining these methods' strengths while addressing their limitations can provide a comprehensive approach to designing ethical AI systems.

To protect sensitive information, practical measures include encrypting and anonymizing data. Implementing end-to-end encryption in health data systems and using techniques like anonymization and differential privacy in research data are effective methods. For instance, Google Health uses advanced encryption methods to safeguard patient data while deriving valuable insights. Internal and external audits should track data sourcing, access, and usage. Techniques such as federated machine learning, data aggregation, and privacy-preserving methods like differential privacy help maintain transparency and security. Federated learning allows researchers to collaborate on medical AI models while keeping patient data decentralized and secure, ensuring compliance with privacy regulations [144].

5.7.3. The Impact of AI on HIPAA

The application of artificial intelligence (AI) in healthcare presents complex challenges and opportunities regarding compliance with the Health Insurance Portability and Accountability Act (HIPAA). AI systems handle vast amounts of sensitive health data, requiring stringent privacy and security measures to prevent data breaches and unauthorized access. While AI technologies enhance data security through advanced encryption, anomaly detection, and real-time monitoring, they must also ensure effective anonymization of personal data to avoid re-identification risks. AI can automate access control and auditing processes, improving compliance and efficiency. However, AI faces challenges in compliance and ethics, particularly in ensuring transparency in data processing and adherence to HIPAA privacy standards. Therefore, healthcare organizations need to carefully integrate AI technologies to fully leverage their potential to enhance data security while addressing privacy and compliance challenges [145].

5.8. Integration with Electronic Health Records

5.8.1. Challenges

When integrating an AI system with an electronic health record (EHR) system Figure 6, significant compatibility challenges can arise due to differences in data formats, structures, and communication protocols. For instance, an AI system might use JSON for data exchange, while the EHR system uses HL7 FHIR, leading to discrepancies in data interpretation. A concrete example is the integration of IBM Watson for Oncology with EHR systems like Epic; data transformation tools had to be developed to convert the oncology-specific data from Watson into a format that Epic could process accurately. Additionally, variations in system architectures can exacerbate these issues. In practice, this means that an AI system developed in a cloud-based environment might face integration hurdles with an EHR system hosted on-premises. To overcome these challenges, organizations often need to invest in custom middleware solutions and extensive testing. For example, the integration efforts at Mayo Clinic involved creating a dedicated interface engine to bridge the data format differences and ensure seamless data flow between the AI system and the EHR system. Addressing these compatibility issues requires not only technical solutions but also a deep understanding of both the AI and EHR systems' requirements and constraints [146].

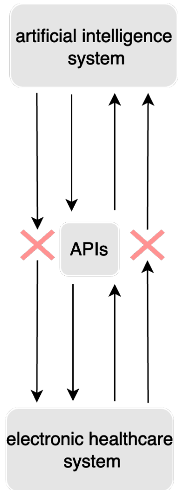

Figure 6. The overview of the AI integration with EHR.

5.8.2. Existing Solutions

Using APIs is crucial for integrating AI systems with EHR systems. APIs facilitate communication and data exchange between the two systems, enabling seamless sharing and access to data. With APIs, AI systems can directly connect to EHR systems to access patients' medical records and health information. This integration allows AI systems to retrieve real-time patient data and use it for analysis, prediction, and decision support [147]. Effective integration of AI systems with EHR systems involves several key aspects. Firstly, developing machine learning (ML) models tailored for specific purposes is crucial. For example, when integrating AI systems for predictive analytics, the models must seamlessly fit into EHR workflows. An example of this is the Mayo Clinic, where AI models are customized to align with the EHR system, allowing for real-time prediction of patient readmission risks based on patient data. Secondly, understanding the technical constraints of EHR systems is necessary. For instance, Epic EHR systems might require data to be processed in specific formats, so hospitals must develop data conversion tools to ensure compatibility with these technical limitations [148]. Governance and regulatory requirements are also important considerations, such as complying with the Health Insurance Portability and Accountability Act (HIPAA) to ensure data privacy and security, as demonstrated by the detailed audits and compliance checks during the implementation of AI tools by the NHS [149]. Evaluating the long-term deployment scope involves planning for the impact and scalability of AI systems, such as the strategic implementation of IBM Watson Oncology across multiple hospitals, ensuring consistent performance and benefits. Additionally, addressing the challenges of changing clinical behavior is critical. For example, the Cleveland Clinic provides training and support to help clinicians adapt to AI systems, ensuring successful integration. Finally, evaluating ML models and their impact on health equity is essential. For example, the University of California, San Francisco, rigorously assesses AI-driven clinical decision support systems to ensure fairness in model predictions across different patient groups. Providing detailed descriptions of EHR interventions is also important, as seen with Johns Hopkins University, which documents how their AI image analysis tool interacts with and interprets imaging data within the EHR system, ensuring transparency and clarity in the operational process [150].

5.8.3. Evaluation of the Existing Solutions

Using APIs to integrate AI systems with electronic health record (EHR) systems facilitates efficient data sharing and real-time data retrieval, significantly enhancing analytical and decision-support capabilities. However, this integration may encounter data compatibility issues, requiring the development of data conversion tools, and must strictly adhere to data privacy and security regulations, such as HIPAA. Additionally, the maintenance and updating of APIs can increase system complexity and require ongoing technical support. In summary, while APIs offer powerful data exchange capabilities, addressing technical and compliance challenges is essential to ensuring effective and secure system integration [151].

5.9. Scalability

5.9.1. Challenges

In the healthcare field, scalability presents a significant challenge for deploying artificial intelligence (AI) solutions Figure 7. While AI applications may perform optimally in small-scale clinical evaluations with a limited data pool, they may face substantial difficulties in maintaining diagnostic accuracy and operational speed when the scope expands to a national healthcare framework. For example, AI systems may struggle with handling large volumes of inpatient data due to the vast amount of patient information, the diversity of medical conditions, and the need for seamless integration with various healthcare information technology systems. To address this challenge, hospitals and healthcare institutions need to implement effective data processing strategies and sophisticated system architectures to ensure the integrity and effectiveness of AI applications at scale [152]. For instance, during the expansion of its AI systems, Mayo Clinic improved system processing capabilities by developing dedicated data processing modules to handle the nationwide flow of medical data, resulting in significant improvements in diagnostic accuracy and response speed. This approach not only effectively managed the issue of scaling data volumes but also ensured the stability and reliability of the system under high-load conditions.

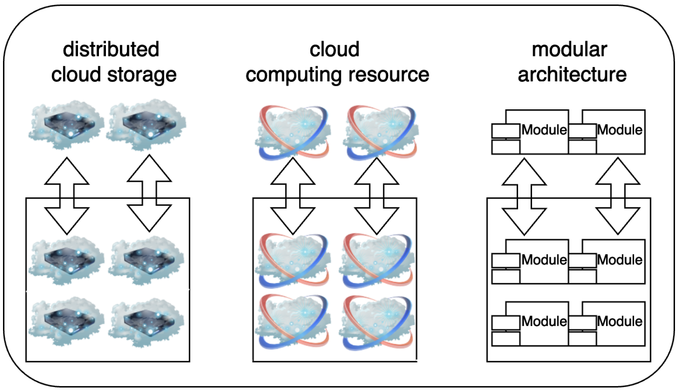

Figure 7. The overview of scalability.

5.9.2. Existing Solutions

The prevalent solution for achieving scalability in AI applications is modular architecture. This approach involves breaking down an application into distinct, self-contained modules, each responsible for specific functions. Such a structure allows for the seamless addition of new tasks or datasets without overhauling the entire system. The modular architecture supports parallel processing of these modules, significantly enhancing speed and efficiency, especially when dealing with extensive patient data. For instance, in a healthcare AI application, the architecture might include separate modules for processing patient data, performing predictive analytics, and generating reports. Each module operates independently and concurrently, which improves overall performance [153]. A practical example of this is the Modular Health Information System at Mount Sinai. This system integrates various specialized modules to handle tasks like patient monitoring, data analysis, and reporting. This modular approach enables effective management of large volumes of patient data and flexibility to adapt to evolving needs without extensive system modifications.

Cloud computing also offers a robust solution for scalability. It provides scalable computing resources that adjust dynamically to meet the demands of AI workloads without the need for expensive on-premises infrastructure. Cloud services deliver scalable distributed storage systems that are essential for managing vast amounts of medical data, which is crucial for training and optimizing AI models while ensuring data security and reliability [154]. For example, Google Cloud Platform's AI and machine learning services automatically scale resources according to workload demands. Hospitals and research institutions use cloud-based solutions to train and optimize AI models on extensive datasets, benefiting from real-time resource expansion and load balancing [155]. Amazon Web Services (AWS) exemplifies this by enabling efficient scaling of computational power and storage for large-scale genomic data analysis, thus maintaining system stability and performance during high-demand periods [156].

However, traditional benchmarking methods, which involve creating a new benchmark for each possible workload, are not scalable or feasible for big data and AI benchmarking. Consequently, new methodologies have been proposed and adopted to address these limitations. For instance, BigDataBench 4.0 and Mystique are designed to evaluate the performance of big data and AI systems more effectively. BigDataBench 4.0 offers a comprehensive benchmark suite for data-intensive applications, including those in healthcare AI. Mystique focuses on assessing the performance of AI systems in handling large-scale data processing tasks. These new benchmarking methodologies create more realistic and scalable benchmarks that align with the practical challenges and requirements of modern AI applications [157,158].

5.9.3. Evaluation of the Existing Solutions

Modular architecture enhances scalability by breaking applications into self-contained modules, which allows for parallel processing and efficient management of large datasets but may introduce system complexity and integration challenges [159]. Cloud computing offers dynamic scalability and cost efficiency by adjusting resources in real time, yet it raises concerns about data security and reliance on external service providers [160]. New benchmarking methodologies improve the evaluation of AI systems by creating more realistic benchmarks for large-scale data, although they require continuous updates and adaptation to stay relevant [161]. The selection of scalability solutions should align with the specific requirements and constraints of the AI application. A combined approach, leveraging the strengths of each method, can address various scalability challenges effectively.

5.10. Underserved and Remote Areas with Limited Connectivity

5.10.1. Challenges

In healthcare, deploying artificial intelligence (AI) in resource-limited and remote areas presents significant technical challenges. Firstly, accessing or utilizing AI applications running on cloud infrastructure becomes difficult due to unreliable or unavailable internet connectivity. Without stable internet connections, AI systems cannot meet their high bandwidth requirements, leading to unmet demands for real-time analytics. Additionally, data collection and uploading processes are affected by unstable networks, severely restricting the learning and updating capabilities of AI systems in these regions [162]. For example, portable ultrasound devices used in remote areas, such as those from GE Healthcare, rely on offline AI for image analysis. These devices can provide diagnostic services without a network connection by storing results locally and uploading them once connectivity is restored. This capability allows doctors to make immediate diagnoses in areas with unstable connections [163]. Therefore, addressing these challenges requires innovative solutions to adapt AI technologies to resource-constrained environments. For instance, some healthcare institutions in remote areas have begun deploying offline AI models to tackle connectivity issues. These models can run on local devices, reducing reliance on internet connections and ensuring efficient diagnostic services in resource-limited settings.

5.10.2. Existing Solutions

To address the aforementioned challenges, in addition to edge computing and fog computing, discussed in the third section of this paper, several other methods can be employed. Firstly, developing and deploying offline AI models can be highly effective. These models, typically installed on local devices or servers, can function independently without needing an internet connection [164]. For example, portable ultrasound devices used in remote areas, such as those from GE Healthcare, utilize offline AI for image analysis. These devices can deliver diagnostic services without a network connection by storing results locally and uploading them once connectivity is restored. This capability allows doctors to make immediate diagnoses in areas with unstable connectivity. Secondly, adopting data compression and efficient data transmission technologies can significantly reduce the amount of data transmitted [165]. For instance, remote health monitoring systems can use data compression techniques like Gzip or Brotli to shrink data sizes, making transmission feasible even in low-bandwidth environments. Wearable devices such as Fitbit employ these techniques to effectively upload health data to servers despite limited network conditions. Thirdly, designing and deploying lightweight artificial intelligence models that require fewer computing resources can be advantageous [166]. Models optimized for low-power devices, like MobileNet and TinyYOLO, can perform real-time processing directly on smartphones and embedded devices, reducing reliance on cloud computing. An example of this is Huawei's Atlas 200 AI accelerator card, which supports lightweight AI models for real-time image recognition and analysis in resource-constrained environments. Finally, implementing low-bandwidth optimization methods can help minimize network bandwidth requirements during data transmission. AI algorithms and optimization technologies tailored for such environments can improve efficiency [167]. For example, in drone data transmission, adaptive compression algorithms adjust data compression rates and transmission frequencies based on real-time network conditions. This method proves particularly useful in disaster relief scenarios, where critical environmental data and video information must be transmitted effectively even with limited bandwidth.

5.10.3. Evaluation of the Existing Solutions

Offline AI models are particularly effective in remote areas with unstable or no internet connection, as they can operate independently. However, they may face limitations in processing power and storage capacity, and data upload may be delayed [168]. Data compression and efficient transmission technologies allow effective data transfer under limited network conditions but may lead to information quality loss and increased computational resource consumption [169]. Lightweight AI models are suitable for resource-constrained environments but may not match the performance and accuracy of more complex models, requiring careful optimization to meet specific needs [170]. Low-bandwidth optimization methods can effectively transmit critical data in bandwidth-limited scenarios but may increase system complexity and computational overhead, and require ongoing monitoring and adjustment to adapt to changing network conditions [171]. In summary, the effectiveness of these methods depends on the specific application scenario and resource constraints. In underserved and remote areas, offline AI models and lightweight AI models offer good local processing capabilities, while data compression and low-bandwidth optimization techniques improve the feasibility of data transmission. The choice of the appropriate method should be based on specific needs, combining the strengths of different technologies to maintain data processing and transmission efficiency and reliability under various network conditions.

6. Conclusions

In this survey, we examine the integration of AI in smart healthcare, emphasizing its evolution from traditional to patient-centric models. We discuss the opportunities that AI brings to the smart healthcare field and its widespread applications. Additionally, we analyze the challenges faced in this domain along with existing solutions. Ultimately, the conclusion underscores that the benefits of AI outweigh these challenges, signaling a promising future for AI in addressing the complex demands of healthcare.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
EHR	Electric healthcare record
ML	Machine learning
DL	Deep learning
NLP	Natural language processing
CNN	Convolutional neural network
RNN	Recurrent neural network
LSTM	Long short-term memory
SVM	Support vector machine
ANN	Artificial neural network
XAI	Explainable AI
API	Application programming interface
FHIR	Fast Healthcare Interoperability Resources

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