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Research Article

Cloud-Enabled Healthcare: A Scalable Approach To Disease Research And Cure Using Artificial Intelligence

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ABSTRACT

Since the inception of the COVID-19 pandemic, artificial intelligence has led to biomarker discovery and causal inferences for clinical outcomes from unlabeled and structured healthcare datasets. Biomedical data are produced in vast amounts and at high speeds, but remain mostly untapped in the absence of knowledge about their origins. A novel, comprehensive, cloud-enabled, collaborative, and automated artificial-intelligence-assisted platform and methodology for early and scalable research, development, and clinical adoption of novel biomarkers, disease subtyping, or targeted treatments from big data is presented. The combination of federated algorithms, standard ontological data representations, and a health data exchange will enable safe, scalable, and ethical research endeavours on sensitive data without transfer of original data. A rigorous and transparent evaluation of biomarker performance in spatial disease locations and through novel notions of clinical validation are designed. This platform bridges instrumented biomedical data production and artificial-intelligence-driven insights, enabling human-scale automated science. Artificial intelligence (AI) has a history of success in domains such as image recognition, where with the advent of sufficient data and compute, some tasks reached human-level performance. Healthcare is often thought naive of such success, both in simple reasoning health tasks and automation of unguided exploration of patient data. Three key, non-exclusive healthcare properties have prevented previous successes of AI. Drawn from molecular medicine, mammographic screening, and the COVID-19 pandemic, an evidence basis is presented, together with a novel clinical AI platform expected to enable scalable, early retrieval of biomedical knowledge. The properties of precision (benign/uninformative) populations, wide-grained, prognostic and inexpensive data, and opaque nuisance variables facilitate cost and complexity reduction in imaging and population biomedicine, while presenting unique challenges in molecular medicine and for a decade-spanning infectious disease. These properties imply a reversible change in the perceived relevance of standalone AI white-box systems. Standard open and fully facilitated app-based systems could now transparently and ethically interrogate semi-rigid inter-instrument discoverable data on fast timescales. An elegant methodology to inform both collaborative human-scale discovery of knowledge and a healthy AI economy is outlined.

Keywords: Cloud Computing,Healthcare Innovation, Artificial Intelligence,Disease Research, Medical Data Analytics, Scalable Solutions, Remote Patient Monitoring, Predictive Modeling, AI Diagnostics, Big Data in Healthcare,Precision Medicine, Machine Learning, Clinical Decision Support, Healthcare Cloud Infrastructure, Data-Driven Medicine.

1. Introduction

Recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency and improve patient outcomes. In clinical care, AI technologies can aid physicians in diagnosis and treatment selection, risk prediction and stratification, and improving patient and clinician efficiency. Although AI methods are prevalent in research, clinical care has been slower to adopt. To

successfully leverage AI in the clinical realm, the analysis must be precise, fast, and robust, and the implementation workflows must be efficient. This requires a large investment in healthcare resources to collect or curate data, which is challenging in resource-constrained environments. Healthcare is also a highly regulated industry, and there are complex requirements for patient safety, confidentiality, and ethics. In addition, privacy-preserving data curation solutions and data quality improvement methods are largely considered to be unrealistic in practice due to intricacies of regulatory standards that vary by geography.
Despite significant investments in collecting healthcare data, translating healthcare AI research into translation is difficult primarily for three reasons. First, existing data sources and collection workflows are inefficient. The increased EHR data availability, but the data is heterogeneous and varied in format. Records are stored in loosely or semi-structured databases by vendors. Sending structured queries to systems is challenging, as the query must fit in a precisely defined structure and runs against existing observations. Second, healthcare data requires significant preprocessing to improve quality and to adopt formats suitable for nearly all AI methods. EHR data often suffers from significant dynamic non-identifiability meaning that data has a significant degree of missingness, misclassification, and errors. This is further complicated by the fact that the most common methods used in healthcare, like deep learning, naturally require massive datasets that necessitate large computational resources that are typically scarce. Both previously mentioned facets require significant investment of costly human effort and carefully articulated procedures. In addition, healthcare is a highly regulated industry, and there are complex requirements for patient safety, confidentiality, and ethics. As a side effect, existing infrastructure and processes to mitigate the two aforementioned complexities are often only implemented with vast resources causing major bottlenecks and cover only a fraction of available data and workflows.

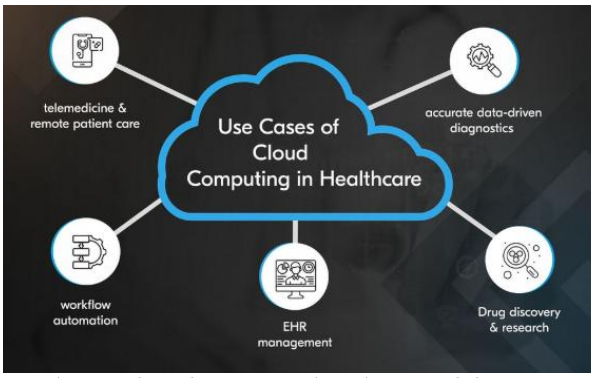

Fig 1: Cloud Computing in Healthcare.

1.1. Background and Significance

Recent advances in artificial intelligence (AI) in healthcare hold the potential to radically alter the quality of patient care, increase patient safety, augment efficiency and, ultimately, improve patient outcomes. AI technologies are well poised to augment healthcare services on many levels, providing physicians with tools to aid them in diagnosis and treatment selection, risk prediction and stratification, and improving patient and clinician efficiency. The past decade has witnessed a vast expansion of the available AI technologies in healthcare, but this has not yet translated into broad-scale changes in patient care. A lack of adequate data quality, scarce resources and a high need for patient confidentiality create significant barriers to translating data science research into this second phase of capitalizing on data science. With the passage of the Health Information Technology for Economic and Clinical Health Act of 2009, a majority of healthcare institutions across the United States have transitioned to electronic medical records which contain a wealth of previously inaccessible structured and unstructured medical data. However, deep learning applications in healthcare remain largely siloed, heavily dependent on skilled technical resources, and resource-heavy to both develop and implement.
Most electronic health record (EHR) systems store patient data in heterogeneous formats. A significant portion of the design and implementation effort typically revolves around extracting, transforming and loading data into machine-learning-ready formats. In addition to structured data for medications, laboratory data, and imaging, there are large amounts of unstructured data like physician notes, discharge summaries, and reports. Currently, there is an acute shortage of conversion solutions that are applicable in healthcare and automate or simplify the data acquisition and transformation process. EHR data has a significant degree of missingness, misclassification and errors. Close to one in five laboratory tests can be miscoded, leading to false conclusions drawn from built models. High-dimensional data like telemetry, EEG, genetic, and continuous physiological data provide highly complex and valuable clinical insights, but require large storage and processing capacity. The data acquisition process for highly irregular high-frequency data streams is often neglected even though these data streams require very careful treatment. It may take one year and close to a million dollars before a model can be trained, and this is often regarded as a necessary trade-off in a data-poor regime. Most healthcare entities lack the interoperability of their data sources, high compute resources, and large data science teams.

Healthcare is a highly regulated industry, and there are complex requirements for patient safety, confidentiality, and ethics. EHR and lab data typically cannot be used outside the healthcare network that owns them. Transferring data across institutions requires weeks of negotiation and the creation of a contract, which can easily exceed hundreds of pages. Furthermore, model benefits must be demonstrated in a way that satisfies current regulations. Compliance with requirements that vary with geography can also dramatically slow the development and deployment of health-related models. AI technologies are very demanding on compute resources, often requiring expensive GPUs and multi-thousand dollar servers. These characteristics of the healthcare landscape provide a very challenging setting for the rapid and efficient development and deployment of AI technologies in healthcare.

2. The Role of Cloud Computing in Healthcare

Recent technological advances in e-Health services, such as Medical Body Area Networks (MBAN), are challenging existing in-house ICT infrastructures. MBANs enable continuous monitoring of patients' conditions by a number of sensors for measuring body signals (e.g., heart rate, electrocardiogram (ECG), body temperature, respiratory rate, blood pressure) on the body, and transmitting those measurements to a central device (e.g., a personal digital assistant, or smartphone) through the IEEE 802.15.6 Wireless Personal Area Networks (WPAN) standard. Body signals collected from patients are analyzed in real-time to monitor their health on a hospital or a healthcare provider's server for historical health condition monitoring and infection control. The real-time health-care MBAN service is also known as eHealth Auto-Diagnosis, a taxonomized e-Health service.

To manage and analyze such massive MBAN data from millions of patients in real-time, healthcare providers need access to an intelligent and highly scalable ICT infrastructure. In particular, they require a computing platform for managing massive amounts of geographical information over a large number of patients. Recent advances in cloud computing have provided a chance for health care to meet such a need. Cloud computing assembles a large network of virtualized ICT services over the Internet. The cloud industry represents companies providing cloud computing services. Services provided by clouds can include infrastructure as a service (IaaS), or platform as a service (PaaS) for middleware and runtime environments and cloud tools. Moreover, software as a service (SaaS) for cloud applications can include business solutions, social tools, and scientific tools.

In health care, cloud computing presents an initial opportunity for health care. Based on pay-as-you-go pricing models, healthcare providers can significantly reduce their initial capital investment in IT infrastructure, assuming they can run on the cloud. An in-house ICT infrastructure using a conventional static design is expensive. For the health care sector, resources from a private cloud are strictly limited and expensive. Regions where conventional infrastructure policies, geography, and ownership do not facilitate e-health deployments require resources that can be obtained with fewer financial constraints from public clouds. Cloud computing greatly improves the utilization of IT resources. So far, cloud computing benefits various sectors, particularly for e-health services.

2.1. Infrastructure as a Service (IaaS)

Infrastructure as a Service (IaaS) is the first and most basic cloud category in public clouds; basic infrastructure resources are provided as services. IaaS provides cloud services that include virtualization, server, networking and storage. The healthcare service platform (HSP) supports self-provisioning and pay-as-you-use. Below are the functions of the HSP: Provisioning generates or deletes virtual machines (VMs) based on templates. Configuration is applied to programming and low-level settings such as amending or rebooting VMs and installation of components. The log function keeps records of changes. Service management checks the status and configuration of VMs and processes. Tenant & user management deals with tenant and user organizations, their designates, and roles. Metering collects resource usage logs such as CPU time, data usage, and the number of used functions. Billing compares the usage data and the pricing policy to generate bills or invoices. Applications and data for each service must reside in a private cloud infrastructure temporarily and periodically. The cloud which stores operation logs and analysis software must be separate from the service engine hosting the running application. Integration of service modules in the same cloud must be carefully considered. Division of workloads, consistent semantics, and data access are some of the concerns.

The HSP was implemented in the IaaS type in EC2 of the AWS cloud. Amazon's Elastic Compute Cloud (EC2) is a service that provides resizable computing capacity in the cloud. If a computer is equipped with physical storage and servers, the EC2 can offer computing resources, resulting in reduced time to create a new virtual machine or computer . The cloud resources can be increased in a few seconds. Monitoring and analytics can be automatically installed and used, reducing costs. It is reliable; instances can be easily cloned to new regions and zones. Changes such as resizing or terminating can be easily implemented without physical disturbance. New computing units can be artificially generated by disabling the previous ones. A pre-existing virtual machine or third-party application can be submitted in AWS format. As a commercial platform, counting, metering and billing are relatively easy. Charged usage detail is transparent to the user. Backup and restoration are easy through automated AMIs. Since basic security provision is built-in, application developers can focus on programming. Data leakage due to complex systems is not an issue due to the public key infrastructure mechanism.

Equ 1: Predictive Disease Risk Score.

$$\text{Risk Score} = \sum_{i=1}^{n} w_i \cdot x_i$$

Where:

- x_i = patient health feature (e.g., age, blood pressure, genetic markers)
- w_i = weight assigned by AI (e.g., from logistic regression or neural network)
- n = number of features

2.2. Platform as a Service (PaaS)

Health Paas (Platform as a Service) offers an open mobile application development platform to healthcare developers. To assist developers in using Health Paas, a sample mobile application based on Health Paas is made available. To specify the architecture of a healthcare cloud platform, the base architecture is presented, followed by a specification of each layer. The healthcare environment is described and a novel architecture for a healthcare cloud platform, which systematically integrates previously ad-hoc cloud services with an aim of managing large scale healthcare data and using them to assist cross-organization healthcare service development, is outlined.

The architecture, consisting of six software layers—Infrastructure as a Service (IaaS), Platform as a Service (PaaS), Software as a Service (SaaS), Discovery service, Service composition service, and Service recommendation service—each of which fulfills a set of functions, is specified. A preliminary implementation of the architecture is described to illustrate the proposed architecture's advantages and effectiveness in managing and utilizing big healthcare data. Verifying the proposed architecture by deploying it in a real healthcare environment and confirming its effectiveness in assisting healthcare personnel and developers in cross-organization healthcare service development is planned .

The healthcare industry is facing major challenges related to ever-increasing volumes of healthcare data, the proliferation of new hardware, software, and communication technologies, little to no interoperability among clinical information systems, and evolving stakeholder needs (e.g., government, healthcare organization, payers, patient, and vendor). The healthcare data boom presents opportunities and challenges to achieve high quality and highly efficient healthcare services taking into account stakeholders' needs. The challenges are exacerbated at regional and national levels given the diversity of stakeholders' incentives whereas data for new services are spread across organizations with different infrastructures, applications, standards, and degrees of maturity.

2.3. Software as a Service (SaaS)

As one of the emerging strategic information technologies, cloud computing is promising for its cost efficiency and its potential to provide quality information services in the healthcare industry. Cloud computing is the use of computing resources that are delivered as a service over a network. Cloud computing features three main types of service: Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS), which provides software applications and data. Cloud service models can be further categorized into public cloud, private cloud, hybrid cloud, and community cloud. The public cloud is operated for the general public or a large industry group and is owned by cloud service providers. Public cloud providers offer a variety of services to consumers, including free-to-free services, free-to-fee services, fee-to-fee services, and fee-to-free services. However, since resources in public clouds are shared by multi-tenancy, they have some serious security and privacy concerns. In contrast, the private cloud is operated solely for a single organization; it may be managed by the organization or a third party. The private cloud has been adopted for organizations with strict security, privacy, and regulatory requirements. With a private cloud, organizations have no concerns about the shared environments; despite this, the higher capital cost of the infrastructure must be considered. However, recent developments in cloud computing have made it possible to create a hybrid architecture, which helps mitigate some of the disadvantages of pure cloud approaches.

SaaS allows cloud providers to install, manage, and operate software applications, leading to lower operation cost and high provisioning to the end-user. End-users do not need to worry about system maintenance, software updates, additional installations, or necessary hardware resources. SaaS is beneficial for end-users because installing software applications is unnecessary, and only a convenient web browser is required. Pay-per-use is the usual payment method, which is advantageous for maximizing investment. SaaS allows end-users to access the latest version of software applications in less than five minutes. SaaS is beneficial for IT providers as well. While traditional software development requires investing a great deal of time, infrastructure, and manpower, careful planning based on SaaS architecture design can minimize these costs. Since software applications are created on the same server and used by remote clients, the server can be more easily managed and updated. In addition to reducing costs and time, cloud computing has the potential to increase sales channels, leading to greater profits.

3. Artificial Intelligence in Disease Research

Diagnosis and treatment of rare diseases face many difficulties, which impair patient care. New technologies in artificial intelligence (AI) are already used to analyze and harmonize experimental data and records in clinical developments, and more are on the horizon. These technological advances may help overcome some of the traditional limitations associated with rare diseases . Strategically, it is recommended to promote cross-industry collaborations and data sharing as well as to activate new platforms for the development of AI applications. To help educate the medical field, the promotion of education and training efforts in AI is recommended to avoid a "knowledge gap" between AI experts and health-care professionals. Research funding is also actively discussed, including possible mission ordinals for off-the-shelf AI solutions with potential for global application to rare diseases. Various technological advancements are currently used strategically for the development of novel treatments for rare diseases. Most approved AI applications in health care focus on medical image processing, while novel AI applications are expected in the fields of disease prediction and prevention as well as hospital operations. All these types of AI allow for efficient and comprehensive analyses of vast amounts of data. They identify patterns and generate insights that cannot be extracted in an adequate time frame by humans. There is a wide variety in type and technical implementation of AI solutions available today as well as concerning currently valid regulations and guidelines.

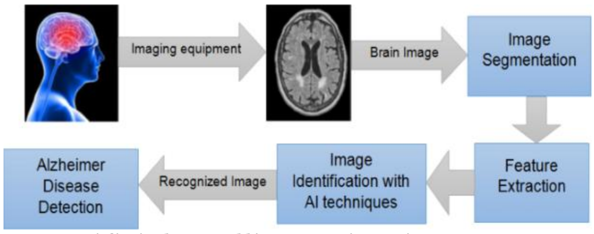

Fig 2: Artificial Intelligence in Disease Research.

3.1. Machine Learning Techniques

Machine learning, a band of artificial intelligence, empowers machines with intelligence by utilizing data effectively. Machine-based systems can either mimic the innate endowments of living organisms or develop intelligence to accomplish specific tasks. They become intelligent when they learn decision-making ability from data without programming, which is an arduous task. Deep Learning is a sub-field of machine learning that realizes the learning paradigm of the brain using deep networks to imitate the performance of the human or animal brain, although the comprehension of intelligence is still unclear. Generally, conventional machine learning refers to shallow learning that works on hand-crafted feature vectors, while state-of-the-art deep learning imitates the multi-layered neuron structure of the brain. The presentation of soft computing technologies boosted the implementation of machine learning in wide-ranging applications over the last two decades, with significant contribution to the healthcare domain .

In healthcare, common machine learning advances have been evolving for years. From computer-aided diagnosis (CAD) to telemedicine, the acting role of information technology (IT) in healthcare is meaningful. AI, or more precisely ML, has been harnessed widely to rescue healthcare. The instant success of ML has taken the world by storm, with the capacity to assist with case triage and diagnoses, enhance image scanning and segmentation, deepen the support of decision making, predict the risk of disease, malignance of tissue, and cancer in neuroimaging .

Since Phillips's call for AI in medicine in 1979, many proposed methods and applications have been published. More advanced and elaborate modeling specifications of AI/ML are confusing rather than clarifying; the believed risks of data sharing are legitimate, but multi-stakeholder approaches are required. This study focuses on ML application to healthcare in the fields of electronic health records, medical imaging, and genetic engineering; these areas also represent healthcare's "BIG" data and have shown significant promise in relation to clinical applications.

3.2. Natural Language Processing Applications

Continuous developments in deep learning have transformed natural language processing (NLP) methods, enabling new ways to leverage unstructured text for analysis. Alongside developments in neural networks have come developments in high-level languages for training and deploying these models. Specialized libraries such as have brought NLP, an area previously thought to be too niche in academia, into public-facing infrastructure. With the advent of cloud computing and assorted cloud platforms, ideas that were previously infeasible because of scale and cost have become practical. Major cloud players such as have made available a staggering amount of compute, enabling large datasets and model architectures to be processed at an unprecedented scale.

NLP technology has the potential to massively accelerate healthcare AI by acting as a means of understanding clinical notes and otherwise unstructured medical knowledge. There are major opportunities for advances in healthcare AI that can be attained only by scaling up to world-class NLP algorithms, hardware, and engineering infrastructure. However, healthcare conversations are sparser and less readily available compared to other

domains. Thus, cloud-enabled approaches to the problem need grounding in a healthcare context and heavily involve language and models amenable to training on a limited number of professional documents.
Most major healthcare institutions have invested heavily in care delivery and management systems equipped with large archival hospitals, medications, allergies, notes, and demographic data. These databases and data stores contain treasures of patient information that can be leveraged for clinical decision support, cohort discovery and recruitment, risk prediction, and many other challenging AI problems. Many hospitals have purchased off-the-shelf third party systems that function as black boxes within healthcare institutions and have developed various data pipelines to extract and synthesize. However, textual notes and clinical narratives are the most rich and informative components of EHR databases and the most stifling with respect to analytics.

4. Data Management and Security

Healthcare is one of the top arenas for cloud computing since it simply cannot afford any loss of either data or its analysis speeds. As with any cloud application, data residing on a cloud may be vulnerable to unauthorized access, misuse, and attack. To cover and bypass such vulnerabilities, a cloud-enabled healthcare data analysis system with a biometric authentication framework is proposed. To speed up the processing of data and to ensure secure, scalable storage and management of the data, cloud computing has been used. Depending on the type and the nominal size of the healthcare data, a tremendous number of different types of data analyzers have been deployed on cloud in parallel. Configuration of the analyzers, and partitioning of the data between the analyzers are done based on a policing agent residing on the cloud. Biometric authentication has been used for both health service provider and patient authentication. While the cloud is relatively new in the healthcare arena, unwelcome incidents and unethical activities by malicious users and unplanned system instances in the cloud have created dubious issues regarding data security, user privacy, and decision making speed at cloud.
Provision of healthcare data analytics as a service from a cloud to a healthcare organization creates multiple issues. It is essential to guarantee that only the users with valid authority access the cloud and it is critical to ensure the authenticity of the healthcare data analyzers residing on the cloud. User's roles and privileges must be specified in order to authorize the healthcare users. On the other hand, storage and online servicing of a huge volume of raw data is impossible even with high-end systems, networks, or expensive cloud resources. On the cloud side, it is a challenge to identify real time demand for data analyzers, and partition and deploy them on cloud dynamically, and then monetize their usage.

4.1. Data Privacy Regulations

In the US, there are several regulations in place at the federal level to protect patient information. The most notable among these is the Health Insurance Portability and Accountability Act (HIPAA), designed to protect any patient’s health information from being used for purposes other than diagnosis or treatment by health service providers. This act safeguards against exposure by allowing only authorized personnel access to a patient’s health repository . However, this is only the most basic layer of protection as further regulations are in place to safeguard data against health service organizations and research entities. The Genetic Information Nondiscrimination Act protects against discrimination against a patient based on their genetic makeup. The National Institutes of Health offers guidelines for omics research and repositories to prevent their misuse. These policies guide the development of algorithms that handle health data regarding its access to third parties, potential alternatives for leveraging the data, and standards of transparency and accountability. The aim is to safeguard patients from abuse of their data and privacy.

The healthcare domain has seen an explosion of data in recent years. The amounts of storage and computation that could be brought to bear on these data deposits far exceed what could be contemplated in years past. Initially, data were collected, curated, and analyzed by one or a small group of entities, but data sharing across public, private, and sectoral boundaries is rapidly gaining momentum - this has also opened up the potential for abuse. Several important questions arise - What are the risks associated with this data-sharing culture? What creative destruction does globalization hold in store for healthcare? What safeguards may protect the health data to be shared across disparate entities? A wide range of stakeholders access, analyze, and circulate health datasets, including state actors, airline companies, insurance companies, employers, corporations, harms, and research organizations. Most notable among these stakeholders are Companies like Facebook, Google, and DataCurity, which collect a variety of user data, including health data, on an unprecedented scale across a wide range of domains.

Equ 2: AI Model Accuracy in Cloud Deployment.

$$\text{Accuracy}_{\text{cloud}} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

Where:

- TP = true positives
- TN = true negatives
- FP = false positives
- FN = false negatives

4.2. Encryption Techniques

Today's healthcare industry is treating human health and living longer life with more happiness. Artificial intelligence (AI) is estimated to secure better results from the data generated in daily life activities like e-commerce, climate change over time, etc. Improving health and living appears a bit complex as no few parameters are available for input like in other fields, and the work of cure and research is very crucial and hard. An effort is made in the paper for a better understanding of health and how best this can be done with more accuracy and scalability with the help of hybrid cloud architecture.

A hybrid cloud architecture using k-2/3 spin glass model at modular level 1 is proposed using local search for loss function minimization and fractionally observable qubits on both local and public cloud quantum devices .The modular structure allows the extensive devices of different capabilities to work in synchrony for obtainability and scalability of very difficult accuracy even over just two parameters having output space more than double that of input space. Simulating this approach for thirty years on classical and simulating architectures is a big question making this research to focus on quantum architecture capacitance.

Encryption approaches usually do not allow processing on encrypted data which implies every time data is processed in its original form. On the other hand, homomorphic encryption allows computation on encrypted data and provides encrypted results to the user. This has many applications in which data is transferred to the cloud service provider for processing resulting in +ve trade-off. Before sending data to any third-party service provider it should be encrypted in a way that even the service provider cannot access it. Thus for the data safety use of encryption approaches is a must but civil provisions. At present there are many public key encryption schemes in which security equivalent hard problems are used and in the presence of no mathematical proofs on correctness and security. But in the healthcare domain as patients keep on changing the health parameters and updating them in less time intervals, the use of cloud computing is growing but data safety seems a risk.

5. Scalability of Cloud Solutions

Artificial intelligence in healthcare has the potential to greatly improve patient safety, efficiency, and outcomes but translating this research into clinical care is hampered by several barriers. The proposed platform employs a cloud-based architecture to provide a collaborative environment while facilitating resource-efficient data harmonization for faster and larger-scale machine learning. As more healthcare data sources transition to electronic records, many institutions will face similar challenges. While recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency, and improve patient outcomes, translating this research into clinical care is often a cumbersome task due to several barriers . These include inadequate data quality, scarce processing resources for high workload machine learning tasks, and high needs for patient confidentiality. Traditionally, there has been a scarcity of big health data sources as most healthcare entities do not have the means or staff to expose these heterogeneous sources to researchers. However, with the Health Information Technology for Economic and Clinical Health Act of 2009, many entities have transitioned to electronic medical records whose constructions often provide a rich medical data source previously unavailable. Recognizing the great potential of these data sources, a great interest in developing algorithms for healthcare data analysis has grown.

Most electronic health record (EHR) systems were initially developed for administrative purposes and as a result, many medical data sources are stored in heterogeneous formats with strict access requirements provisioned by creative legal mechanisms and legacy systems. The lack of balance between the plethora of state-of-the-art tools and the sparse infrastructure for implementing them results in a large amount of misclassified, erroneous, homogeneously formatted data. In addition to the structured data for medications, laboratory data, and imaging, a multitude of unstructured data generated by the physicians, such as physician notes, reports, and discharge summaries.

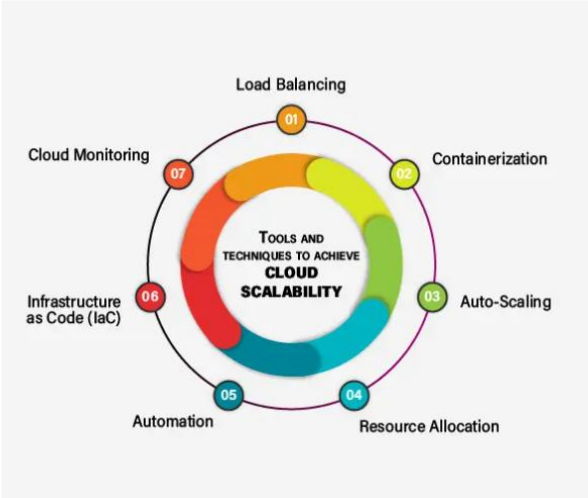

Fig 3: Scalability in Cloud Computing.

5.1. Elasticity in Resource Allocation

The cloud-centric architecture proposed in Section 3.3 has a wide elasticity in resource allocation. It challenges commonly used threshold-based reactive models, which are inadequate for predicting resource demand in healthcare systems due to unpredictable, abrupt spikes in resource demand that can lead to critical situations. Proliot is a modeling approach combining cloud and high-performance computing to address the IoT scalability problem in a novel EPCglobal-compliant architecture. The model offers an elastic EPCIS component that is automatically allocated or deallocated concerning the system load. A predictive approach is proposed to forecast the expected system load by means of Autoregressive Integrated Moving Average (ARIMA) and Weighted Moving Average (WMA) . In addition, a heuristic-based method is conceived for the tornado situation, indicating the load behavior and anticipating scaling in or out operations. Experiments suggest that Proliot improves 300% the response time when compared with the scenario that is not using elasticity. The state-of-the-art prediction methods (ARIMA and WMA) achieve between 3.09% and 168.498% improvement in the F1 measure when compared to the conventional threshold approach.

5.2. Cost-Effectiveness of Cloud Solutions

The cloud provides a feature that many local server installations lack: scalable access to processing and storage capability that expeditiously grows to meet the needs of demanding analyses. It allows small initial investment and can be cost effective depending on usage patterns. A question of cost metrics: Are costs for cloud services within the local budget? Are these costs less than owned server capabilities? Is the cloud an ideal setup for ongoing expertise needs? A concern of sustainability: How do external relationships work? Is limited access via grant supporting the project expected? Are projects dependent on private vendors holding personal data? These considerations favor partnerships with academic institutions with a history of strong infrastructures, branding, and policy. Spoken or unspoken rules governing academic cloud use differ markedly from those in the private sector. Initially, an institution may need to absorb costs of usage and build expertise in moving to cloud use. However, the use of privately held data should be limited and shared with academic partnerships. Public Cloud Model: Used extensively for storing and processing objects; growing awareness that the size of data is large, variable in complexity, distribution of access, and security, thus, are the costs to deliver the object. Servers distributed geographically are more expensive and complex. Computer capacity is elastic, adjusting to the demands of the user. This raises a question in a grant funded model of large fixed data expenses or load balancing and cost access structures. It is easy to underestimate downstream costs. In the case of the cloud model limits access to Federated Query requests rather than a Cloud front implementation that may cover the costs of compute and access.

6. Case Studies in Cloud-Enabled Healthcare

The most reliable and straightforward use of a cloud-enabled platform for cloud-based AI development and use in a clinical setting is the integration of large public AI models, enabling healthcare providers to leverage the capabilities of different imaging modalities and a variety of model architectures. The simplest use of Clio is providing a note-taking interface with additional customization options, speeding up the documentation process. Clio is already integrated into a few institutions, where it caters to the pediatric population. However, beyond that, these models could be adapted to accommodate additional input data sources, such as reports from other systems or additional medical data types, such as pathology.

Another more ambitious project that exploits an entire cloud-enabled platform entails its repurposing for tagging cardiac biomarker time series data. While it only uses text to create tags on an event-basis, additional inputs like video and audio can be incorporated. Further, the results obtained from different models can also provide the basis for ensemble tagging, which could lead to training datasets that are substantially more capable than any one model could produce.

Equ 3: Cloud Resource Utilization Efficiency.

$$\text{Throughput} = \frac{\text{Total Data Processed (GB)}}{\text{Time (seconds)}}$$

6.1. Telemedicine Applications

Healthcare is changing significantly because of the rapid adoption of eHealth and mHealth technologies. Researchers are studying how patients' interactions with technology affect the results of diagnosis and treatment, while practitioners are looking for innovative ways to make the most of information technologies, such as automatic tweets for sending personalized messages to patients about medication reminders, health education, and attendance improvement . Telemedicine seems to be the way forward. Through video consultations, telemonitoring, and remote diagnosis tools, patients can receive medicine from the comfort of their homes, which helps operators improve productivity and create new services that can be provided.

In recent years, there has been a growing interest in telemedicine concerning patient empowerment and adherence to treatments. Patients need to be concerned with their own health to adopt a correct lifestyle, which can be facilitated by ICT tools. Furthermore, operative healthcare configurations where patients play an increasingly active role in the provision of healthcare services are emerging. For example, multi-disciplinary platforms for chronic diseases allow users to visually navigate their own health through pictures, trend-line graphs, and object metaphors, as well as compare and communicate their data with other users.

The increasing importance of remote care services based on telemedicine to improve quality of care, patient adherence, and cost efficiency is a key factor in shaping this emerging field. Traditional opinion mining and text analysis techniques are often ineffective due to limited coverage, language issues, and real-time requirement for user-generated data. In this context, novel deep learning strategies are investigated that combine tools for understanding multimedia content and social network structure with state-of-the-art opinion mining techniques to enhance telemedicine service. The resulting system presents a multi-layer coarse-to-fine architecture integrating deep learning recommendations and social network analysis methods with expert opinion discovery.

6.2. Remote Patient Monitoring

The growth of IoT technologies and networks resulted in research and applications in the medical field, as hospitals and clinics are approaching the era of remote patient monitoring. The remote care system offers various advantages to doctors and patients, including increased accessibility to patients' health data during difficult situations and improved continuity of care. The traditional medical system mainly depends on healthcare professionals, which are time-consuming and costly, making it cumbersome to design a personalized treatment plan to cure chronic diseases. Moreover, dealing with the timely identification of patients' health deterioration becomes a bottleneck with the increase in patient number and healthcare data diversity. Here, by analyzing the health statuses and their trends on the cloud with AI and ML technologies, potential dangers in a patient's health can be accurately predicted, and doctors can proactively intervene in each situation. However, IoT healthcare applications for monitoring patients and their diseases are ubiquitous but face unique challenges related to modeling and dealing with large data.

To address both challenges, this study proposed a cloud-enabled remote patient monitoring model, which is an end-to-end solution for interaction with IoT medical devices and deeply analyzing the health conditions of patients on the cloud. In this model, a personal cloud server was established for balancing the load between the cloud and edge servers. Moreover, the model contains extensively designed procedures, parameters, and knowledge, which are efficient in monitoring diseases while properly managing data utilization. By evaluating the model's effectiveness on a real IoT testbed with multiple sensor nodes, it was demonstrated that the model could efficiently extract meaningful insights from patients' health data. On the cloud side, a practical case study was presented to illustrate the potential of the knowledge representation, and the study extended the whole health status analysis into future predictions.

Although the remote health monitoring model can sense and analyze diverse medical data from a large number of patients in real time through the cloud, this research still has some obvious constraints. First, health devices have stringent energy constraints. Most of them can only work for around 24 h and role as data generators. For prolonging battery life, a schedule on each device is required, and at each time interval only a specific set of sensors is allowed to send data. Second, the model was demonstrated in monitoring a specific disease, diabetes. Though it is easy to extend to other diseases, not all human diseases can be treated in this way. Keeping a watching database of patients' health and the analysis models would be cumbersome and impractical. In the future, the model's scalability is feasible by training the physiological knowledge based on population data, which groups different patients into classes, and when a new patient appears, he/she can be fitted into the most similar class.

7. Challenges in Implementation

Recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency and improve patient outcomes. AI technologies can aid physicians in diagnosis and treatment selection, risk prediction and stratification, and improving patient and clinician efficiency. Typically, data science research is conducted on diverse medical turn-key datasets that are pre-processed to a standard format and do not suffer from the aforementioned issues. Whereas access to a few national public datasets is usually insufficient to train deeply parametric machine-learning (ML) models, obtaining access to real-world clinical data is challenging. In particular, harmonizing diverse data sources is a very time-consuming and resource-heavy process, which hinders the translation of medical data science research to real applications and substantial patient benefits. Institutions that own and maintain large quantities of medical data like hospitals, pharmaceutical companies, and research institutions are regarded as having "data wealth." On the other hand, most healthcare entities lack interoperability of their data sources, high compute resources, and large data science teams. As a consequence, the gulf between data-rich institutions and data-poor institutions widens constantly, and the unrealized potential of the vast wealth of clinical data continues to grow year by year. Achieving significant early successes and developing the necessary relationships and revenue streams is essential for the future sustainability of the platform.

Healthcare is a highly regulated industry, and there are complex requirements for patient safety, confidentiality, and ethics. EHR data often contains sensitive patient information, which must be securely stored, anonymized, and handled by authorized personnel. Information technology systems in healthcare organizations need to ensure that patient data is accessible only to authorized personnel, and that there are audit trails that track access to patient data. Data and models cannot be accessed outside the organization premises. Only aggregate reports can be shared, unless otherwise permitted. It is very difficult to collaborate on sensitive data outside healthcare institutions. Using a clinically useful model usually requires access to the native patient data, and its "black-box" nature is not conducive to trust building. Additionally, architecture, infrastructure, and requirements often differ between organizations. As a result, interoperability, distribution, and transferability of AI-in-healthcare technology is problematic.

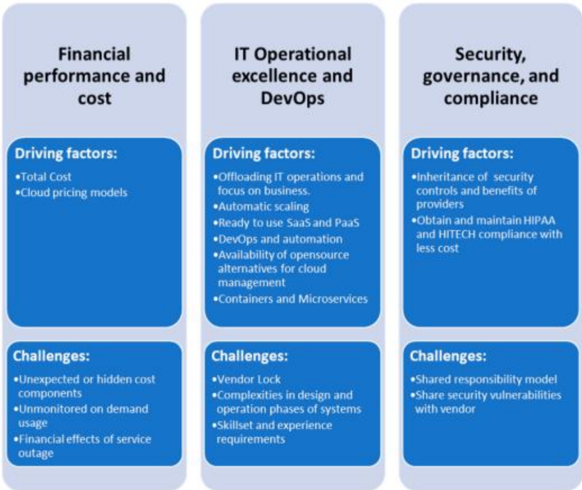

Fig 4: Challenges and Opportunities in Use of Cloud Computing for Healthcare Systems.

7.1. Technical Barriers

Recent advances in artificial intelligence (AI) in healthcare have produced technology poised to revolutionize patient safety, augment efficiency, and improve patient outcomes. Healthcare AI falls into four main categories with numerous use cases that could be translated into successful products: diagnosis and treatment selection; risk prediction and stratification; and improving patient and clinician efficiency. These technologies would need to be trained on extensive and varied datasets but deep-learning-enabled approaches to disease diagnosis, treatment selection, and prognosis prediction have shown promise when trained on large healthcare datasets that include patient examination, lab test results, medication records, and other clinical interactions . These datasets provide unique data characteristics: heterogeneous combination of structured and unstructured datasets, need for extensive data cleaning, and a semi-volatile nature. There are significant barriers to leveraging this data in but not limited to: inadequate data quality for machine learning, scarce resources for machine learning and clinical expertise in any given council, and very high patient confidentiality needs. To significantly improve patient safety, efficiency, and hospital-scale patient/physician-centered healthcare outcomes, a system that automates the clinical data acquisition and processing into machine-learning-ready datasets in an efficient, transparent, user-friendly, real-time process at scale has been created. The objectives of this proposal design were scalability to overcome the significant data needs and generalizability to handle heterogeneous projects of diverse clinical institutions as the main requirements for this system. Achieving these objectives yields a low-friction platform that focuses on iterative collaborative processes to facilitate the early-stage healthcare AI research and rapid prototype developments are described. The described platform would significantly reduce the time to model completion from around two years to six months using mainly the existing data science resources and thus create opportunities for faster AI integration in clinical care to meaningfully improve patient outcomes.

7.2. User Acceptance Issues

Despite mounting interest in applying machine learning models to medical data, several issues persist. The volatility of data-controlled properties can exacerbate irregular access and unpredictable latency problems. The growing complexity of medical data would result in many diverging local vaults. Maintaining a high data management complexity can discourage researchers from utilizing their institutional vaults. Disentangling heterogeneous methods can lead to non manageable file sizes, explaining why medical files are often disjointed. Health care practices increasingly rely on digital media, spurring the looming demand for storing and sharing vast amounts of medical data in an interoperable fashion. As the complexity of digital data storage systems grows, so does the risk of encountering barriers to accessing, retrieving, and processing medical information. Recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency and improve patient outcomes. In clinical care, AI technologies can aid physicians in diagnosis and treatment selection, risk prediction and stratification, and improving patient and clinician efficiency. Barriers to translating data science research into patient care include inadequate data quality, scarce resources, and high patient confidentiality needs. Many institutions have transitioned to electronic medical records systems that provide a rich medical data source. Unfortunately, most electronic health record (EHR) systems store patient data in heterogeneous formats, sometimes even combined with legacy systems. The EHR data has a significant degree of missingness, misclassification, and errors. Harmonizing these diverse data sources can be a very time-consuming and resource-heavy process. Moreover, healthcare is a highly regulated industry, and there are complex requirements for patient safety, confidentiality, and ethics. These characteristics of the healthcare landscape present significant challenges for the rapid and efficient development and deployment of AI technologies.
To address this complex scenario, buttressed by stricter regulations, a platform pooling clinical data in a decentralized fashion for comparative efficacy research became increasingly attractive. This approach permits sensitive personal health data to stay in local hospitals while messaging only metadata defining the model and how to apply it to the local vault. Resulting information flows only from coordinated learning. Despite significant technical challenges, this strategy produces a more comprehensive model while granting maximal privacy.

8. Future Trends in Cloud-Enabled Healthcare

As future trends of cloud-enabled healthcare reshuffled many aspects of research towards enabling useful real-world applications, researchers mostly focus on the selection of ML/AI models for new applications, algorithms that work novelly in various healthcare environments, fully connected systems that could satisfy some typical types of queries on heterogeneous big medical data, resource management policies, etc. However, not so much has been paid on how to improve the involved cloud or edge computing platforms themselves. In this section, future trends of cloud or edge platforms themselves, tested with synthetic performance measures, research gaps, feasibility and reasoning into the future for ensuring these applications bringing real value to healthcare, are also discussed. The performances of many existing applications deteriorate heavily with the scales of systems and data sizes, and the expansions of applications may ruin whole systems due to not so reasonable design choices. There is still a lack of main research efforts on designing cloud-enabled healthcare systems with guaranteed scalability. Much should be done to analyze and elaborate more lightweight algorithms for better fitting existing healthcare platforms and infrastructure and to combine cloud and edge computing effectively for larger return applications. Even for one cloud-based platform, it often consists of many subsystems, among which, some may not design in a robust and solid way, possibly falling into situations of capability exceeding easily when looking for meeting performance requirements with larger volumes of data processing. Deep learning emerged as useful substitutes of traditional analytics or even hybrid methods composing a combination of much advanced so-called “black box” analytics or systems for real-time healthcare analytics. However, researchers still need to better understand and thoroughly evaluate and justify usage of deep learning with clear theoretical runtime guarantees and medical data-specific analyses, as such intricate systems and key parameters may result in equity issues toward accessibility and feasibility. In addition, growing extensive literature on personalized medicine does not discuss potential impacts and positive changes brought by it in the applications to some specific health outcomes, treatment levels, and societal patterns.

8.1. Integration with IoT Devices

The healthcare IoT devices build a big amount of data from the patients monitoring units. The cloud resource is used to store the healthcare patient's data for decision making and diagnosis support for the long term. Data are transplanted organized details in a systematic arrangement of IoT devices to the cloud to make available with existing data. Cloud aggregation is disintegrated by which the data are nationally group data. The health medical organizations get the ability to deliver fine-grained regularly hybridized personal cloud services from the cloud. An automatic healthcare services processing mechanism for delivering the fitting medical care tidings is proposed in which the untamed healthcare devices detecting processes are utilized. The service discovery is processed in a rapid and dynamically evolving process to conclude the moment users need by the system. The methodology is illustrated to be advantageous based on the experiences from practical applications in a smart health procedure. The present day portable smart health service through timely delivery with an agile service matching system is proposed. The hybrid portable and fixed smart health care system is designed to detect various health data as well as commonplace wellbeing conditions. The comprehensive analytic approaches for service analysis and rapid service discovery based on fine-grained service description with event detection and confirmation is elaborated. Cloud computing is the on demand availability of computing resources that already have been established in cloud computing systems. A system that uses this technology is called a cloud, math clouders are set in a cloud computing system having similar infrastructure deployments. The efficiency of healthcare's content is reportedly increased after the use of cloud systems. A comprehensive analysis of integrated health services has been conducted. It is directed at converging on acknowledging acceptance undertakings to reach extents such as system analyses or trend monitoring.

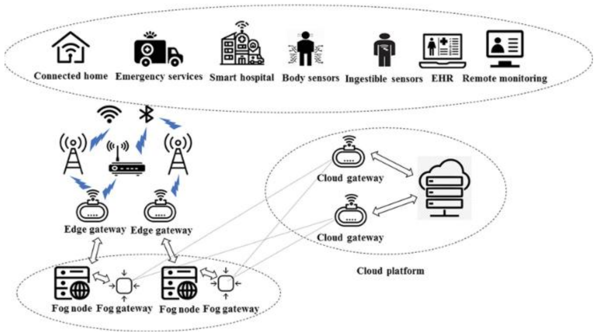

Fig 5: Healthcare system based on IoT and cloud computing.

8.2. Advancements in AI Algorithms

New AI algorithms are emerging, with two recent examples on data retrieval and data generation being presented to show how AI can be implemented in disease research and cure generation. One goal is to expedite current drug generation efforts targeting specific diseases or diseases previously understudied. Whereas current efforts may take large state-of-the-art supercomputer GPU clusters on the order of six months to generate drug candidates, the AI methods presented here will attempt to push that time scale down to one to two days, with substantially lower compute requirements.

Translating ontology represented by natural language sentences to data retrieval queries is an active area of research. To prevent misunderstanding and misappropriated results based on a misdirected query language translation, a natural language-to-SQL translation algorithm has been selected. The algorithm was tailored to cancer data stored in a Presto electronic medical record database. The resulting model is a traceable query neighborhood model designed to closely mimic human reasoning, using the similarity of many queries to find the output of a new query.

Generative AI techniques are highlighted with a focus on modeling anti target and bioactive compounds. This component, firmware from many generative approaches, is critical to drug generation. The goal is to accelerate drug generation targeting bacterial infections and other important disease areas that have so far seen little research investment. A model based on a recurrent neural network generative model generating molecular SMILES was applied. This primitive model provides a toy proof of concept, but refinements and new ideas are presented to address challenges, such as slow training, low fidelity of output compounds, and biologically irrelevant output during inference.

AI is on the rise in areas such as drug discovery and development, image-based disease diagnosis, and the analysis of large datasets to accelerate various areas of biomedical research . AI has been used extensively in both basic and clinical research. AI technology has shown its promise in increasingly important areas, such as drug discovery and development. There are concerns that rapid advancements in AI technology might outperform or replace the work of physicians, the traditional healthcare expert in the biomedical field. However, the essential algorithms and models that deliver results to healthcare researchers in these rapid advancements are often of little help to critical users.

9. Ethical Considerations

A wide variety of options for ethical principles are considered. One of the most cited approaches is the four principles of bioethics of respect autonomy, beneficence, nonmaleficence, and justice. A need for new ethical principles has arisen due to the rapid change in the inclination toward AI and ML in healthcare and uncertainties regarding a future with such innovations. To this end, principles that overlap with basic rights in law but are assessed from an ethical perspective or ethical principles of health promotion for relatively lower-level stakeholder obligations are considered as options. The consideration of AI principles expands the scope of possible content for ethical principles. Focusing on ethical principles for AI designed to be implemented in the healthcare domain can effectively guide the design of an AI tool in a manner that abides by ethical requirements while achieving rudimentary propositions of good AI design. Ethical principles for non-Big-tech companies developing AI for healthcare service are closely tied to the ethical principles outlined in law and regulatory guidelines that determine the legal compliance of such innovation. Safety in AI research refers to the ethical use of personal data and the means of AI generation development. Because of the nature of AI and its social implications, safety in AI also embraces the risk of effects broader than loss of autonomy and unintended harm. Indeed, some effects may pose a serious danger of material damage at the global level. An ethical health policy regarding AI in healthcare service should therefore address the global risk of AI as health and the ethical accountability of litigations regarding AI malfunctions with serious consequences. Changing healthcare systems for a probabilistic announcement of better treatments with a less clear warrant lengthens the distance to society. The assessment of expectations in AI generation development is indispensable to realize that future. This implicitly requires statements on trade-offs, the increasing role of government in healthcare, and decompounding measures.

9.1. Bias in AI Algorithms

Machine learning (ML) plays an increasingly beneficial role in multiple multidisciplinary fields including natural language processing, computer vision, and speech recognition. Healthcare applications based on ML and artificial intelligence (AI) models are leveraging cloud-enabled technologies to accelerate multi-canonical analysis of health data for decision support and outcome prediction. Yet, traditional architectures of AI algorithms in healthcare are based on vertical data architecture where AI developers typically rely on specific data silos and local installations, resulting in poor clinical efficiency, conversion, and scalability. Closed and stranded local AI algorithms cannot avail themselves of real-world, ever-growing, diverse datasets required for generalization and robustness. When trained on biased datasets, these algorithms tend to produce biased results with few generalizations. Consequently, AI developers of these algorithms tend to overstate their performance and applicability to ensure adoption.

The proposed cloud-enabled, multi-canonical platform with Healthcare AI-Assurance will reduce biases across all healthcare AI applications before and after deployment. A novel dual-layer architecture is proposed for decentralized training and federated AI algorithm deployment on the cloud. Third-party federated learning monitors, AI result explainers, and surrogate test data generators are incorporated within the architecture, along with data provenance and ownership-based generative and diagnostic biases, to ensure ML models generated on this platform are the least biased when fed with biased datasets in the wild . It provides a unique opportunity to alleviate unwanted biases in AI algorithms. Additionally, a clinical decision support system (CDSS) on the platform will address challenges faced by the traditional point-of-care CDSSs that rely solely on rule-based clinical pathways in the big data scale e-Health regime, providing large-scale, personalized health outcomes prediction and decision support on the cloud. With the broad development of the proposed platform, this approach will contribute to a scalable approach to healthcare AI research and applications.

9.2. Informed Consent in Data Usage

Informed consent protections vary widely from state to state and country to country. Some agree to share data used for AI research at the level of aggregate summary statistics. Others want the flexibility to share any PHI as long as the researchers interpret it under a data use agreement (DUA) that includes technical and administrative safeguards like encryption and fingerprinted access. Some simply ask to be contacted directly before any data sharing, allowing them to opt in or out based on a topic. Whatever the local regulations, as AI health research expands beyond academia, the demand for public trust in the use of other, less used, permissions is gaining prominence. Patient organizations have launched an inquiry on whether and how researchers using AI should be required to show that they have approached the research subject at some point in the not too distant past and that the proposed studies have passed their informed consent standard.

Shared data HK was established based on Matomo to give patients free control over their data generated in the system in aggregate and for research/analysis. Controls are a 3–6 button hierarchy for sharing vs hidden control with broad categories for inference or classic phenomenological analysis with an option for the website to get approval before any share without any sub-policy. The patient-driven organization dropped all EXFetcher bots. Only Matomo can generate anonymized records for web traffic analytics or API queries to the argument AI, and non-differentiating aggregate computation by burst licensing. In the coming decade, all cases and aggregates of share and use should be tracked for records, regular audits, and later local sandbox analyses for precedence audits. In response to cases of abused sharing, all shares will be stigmatized with a ratio to the DV-x, preventing all future shares. Broader precautions include environmental controls for server farms, third-party AI with no outside query access, restriction override procedures, AI holders reporting intention, real-time targeted alerts for ML conflict zone queries, signature-based informational flow detection, and multi-step verification for the records of transnational “quiet” requests.

10. Conclusion

Recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency and improve patient outcomes. In clinical care, AI technologies can aid physicians in diagnosis and treatment selection, risk prediction and stratification. Within academic institutions, healthcare AI research can promote optimization of withdrawn materials and resource-intensive methods. Lastly, this technology can be harnessed to reduce administrative burden associated with the writing of clinical documentation. However, many institutional data science teams are bottlenecked by a lack of validation datasets or ground truth labels required for supervised AI model development. To facilitate healthcare AI research at scale, cloud-enabled platforms must be constructed that facilitate modification of and collaboration on large datasets. While such services exist for general use, they have not yet been adapted for the underground needs of the healthcare community. Healthcare entities evaluate oscillate, heterogeneous electronic health records that require coordination to synchronize, harmonize, and standardize for analysis. These data sources often contain sensitive patient information; rigorous testing and quality control must be executed before they can be shared across institutions. In this study, a focus is placed on constructing a cloud-enabled platform that supports the research and development lifecycle for healthcare AI models across diverse institutions. It is organized around standard use cases to assist with data sharing and transfer, data cleaning and preparation, exploratory analysis and model development of healthcare data science workloads. The platform has been scaled and adapted to conform with the security, compliance, and ethics requirements imposed by the healthcare restrictions on data governance, robustness, and standards. This platform can help ensure that in academia and healthcare AI research, state-of-the-art model development occurs in a timely and efficient manner that does not over-extend or burden institutions for data science. Maturity models outline the evolution of the development of the platform components and the AI research capabilities. There is hope that with the deployment of these components, healthcare AI research can be conducted on a self-serve basis using ad-hoc registered components .

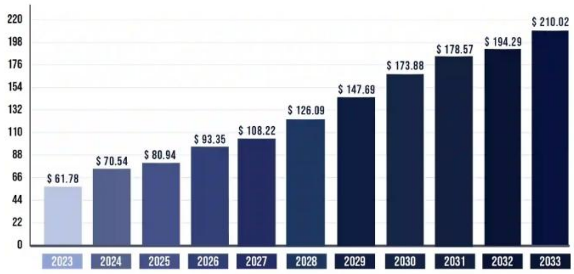

Fig 6: Cloud-Enabled Healthcare Using Artificial Intelligence.

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