Integrating AI and Big Data in Healthcare: A Scalable Approach to Personalized Medicine

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Abstract
Currently, healthcare is lacking in access to care, differing quality, and doctor shortages, which are increasing on a global scale. Some presented artificial intelligence (AI) as the solution to problems in healthcare. The state of AI in predictive and proactive interventions in healthcare and clinical decision support systems (CDSS) has been discussed. The majority of this work focuses on the progress of AI in healthcare systems ranging from radiology to surgery. Some debated how AI could be used to fill the human resource gap in medicine by integrating AI with medical professionals, enhancing diagnostics, and helping with better decision-making. Ethical implications (EI) of utilizing AI technology as an integrating part of the healthcare system have also been highlighted as it is crucial to address these issues ahead of time. Moreover, there are many challenges worldwide of implementing AI in medicine. The obstacles and caveats of AI in medicine in general, and some specific areas like radiology, pathology, dermatology, and others were talked about. Furthermore, current challenges of the field of life sciences that could be solved using algorithms, such as detection and isolation of rare cells, and analysis of multi-omics data were discussed. Analyzing the biomedical literature written in natural language for drug discovery, predicting off-target effects of specific compounds, etc., using were included as some successful implementations and techniques to facilitate AI and in biosciences. There are also some limitations and formidable obstacles of AI, such as data privacy and security issues, uncertainty in the usage of black boxes of algorithms, and the state of AI hype in validation. AI or is recognized as a branch of AI that contains algorithmic methods to think of solutions, retrieve results, and resolve scientific problems whether in healthcare or others.

Keywords: Artificial intelligence, big data analytics, personalized medicine, healthcare data integration, machine learning in healthcare, predictive healthcare models, scalable health systems, data-driven diagnosis, medical data processing, clinical decision support, healthcare informatics, patient-centric care, precision medicine, real-time health monitoring, health data scalability, electronic health records (EHR), AI-enabled diagnostics, genomic data analysis, population health management, data interoperability.

1. Introduction

Most diseases, including chronic ones, arise from the overall disease process arising from complex interactions between genetic, epigenetic, environmental, and risk factors. Generally, there is a gradual onset of subtle metabolic abnormalities and the appearance of a cohort of pathological markers, which provides a window of opportunity for early detection, prevention, and intervention. Any multi-factorial disease involves a reasonably large patient cohort. Current technologies such as sequencing, imaging, laboratory assays, digital health information, and wearable devices allow the collection of multi-modality and large-scale patient information. Artificial intelligence (AL) and big data enable the prediction of disease progression pathways from the wealth of natural patient information. A basic problem in precision medicine is how to identify individuals at risk or with early onset of a disease or distinguishing sick individuals from healthy ones in a large patient cohort. This involves analyzing each cohort of agile but non-interpretable data sources and corresponding patient information. Early identification of potential patients is a non-linear classification problem based on multi-modality, heterogeneous, high-dimensional, and time-series data signals.

Some broad features of a cohort of aging individuals with personal data such as biometric, genomic, lab, history of chronic disease, medication, and lifestyle are recorded in health records. Advanced technologies and analytical tools have tremendously minimized existing constraints in utilizing healthcare information for healthcare decision-making. Precision medicine often relies on transformations of routine and unstructured health records in natural language into structured data, which renders it virtually unapplicable in many critical settings. In addition to the heterogeneity of patients or health systems and scarcity of domain knowledge or expertise for model training, the sheer size of health records creates scalability and interpretability issues. The accumulated data dwell in disparate systems, each with its system features or retiring models. Moreover, much health record data drift with time such that supervised or semi-supervised model training convergence becomes a concern. Lastly, the health industry and health consumers may think that a health-tech company is using AI to run some magic, which invokes ethical issues.

2. The Role of AI in Healthcare

The use of artificial intelligence (AI) within healthcare systems on a global scale is undeniably gaining traction. The bottleneck for the effective adoption of AI in healthcare is the availability of data, and the recent advancements and availability of big data within the healthcare industry represent a critical opportunity. There has been a surge in digital health applications where information and communication technologies (ICTs) are used to manage illnesses, health risks, and promote wellness. In healthcare, many such applications include wearable devices, mobile health, telehealth, and telemedicine. This evolution brought about by the proliferation of ICT has the promise to improve access to healthcare services, reduce inefficiencies, and provide more personalized healthcare. These opportunities come to fruition by widening access to patient data, which is crucial to develop smart digital health applications and inform effective decision-making on prevention, diagnosis, treatment, and follow-up.

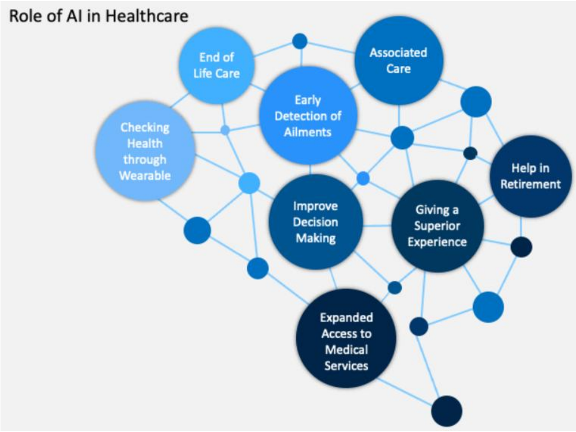

Fig 1: Artificial intelligence in healthcare

By definition, AI applications must be trained using clinical data, which may be real patient data or synthetic data. There is a wide variety in the range of clinical data that may be available from a variety of sources including demographics, medical notes, physical examinations, and clinical laboratory results. Along with the emergence of advanced analytics, machine learning (ML), and AI techniques, there are numerous possibilities for transforming these data into meaningful and actionable results. In addition, data from wearable devices and sensors provides opportunities for more personalized healthcare by implementing proactive/preventive health. More specifically, these data enable the consideration of risks and symptoms that are more crucial to an individual patient. For instance, decisions on stroke prevention and treatment depend on individual symptoms, medical history, risk factors, and social characteristics such as living area and behaviour patterns currently unconsidered. Reasoning on individual patient data should align better with diagnostic reasoning in healthcare to provide more useful recommendations.

2.1. AI Technologies in Medical Diagnosis

The paper surveys the literature on artificial intelligence in disease diagnosis. The goal of this survey is to comprehend, organize, and analyze how artificial intelligence methods have recently been employed in disease diagnosis, particularly in breast cancer, diabetes, cardiology, Alzheimer's disease, and other diseases. After providing a synthesizing framework that organizes and analyzes 174 papers published from 1941 to 2021, it proposes a future research agenda to facilitate scientific advancement in this important and timely field. Artificial intelligence (AI) has transformed various fields, as evidenced by its remarkable success in numerous endeavors, particularly in the financial, business, and healthcare sectors. The dominant method for implementing artificial intelligence is machine learning, which provides a variety of supervised and unsupervised learning algorithms for data-driven modeling. The concept of AI-based disease diagnosis refers to the development and use of AI methods to analyze patient data for the purpose of assisting clinicians with the diagnosis of various diseases such as Alzheimer's disease, breast cancer, diabetes, and cardiology. A broad survey of AI-assisted disease diagnosis is thus warranted. While there are some general surveys on AI and biomedical informatics, as well as reviews on a particular disease and diagnosis approach, to the best knowledge of the author, there are no comprehensive surveys on AI-assisted disease diagnosis focusing on how AI methods have been applied to this specific field.

The surge in digital health applications, where contemporary information and communication technologies are used to manage illnesses, health risks, and promote wellness, has grown exponentially. This includes wearable devices, mobile health, telehealth, and telemedicine. This evolution has the promise to improve access to healthcare for those who previously did not have access, and to provide more personalized healthcare. Traditionally, healthcare is reactive. Currently, compliance with prescribed medication regimens and regular check-ups at the physician's office do not lead to behavioral changes to increase wellness. There is a need to target patients or populations with a higher risk of eventual disease in order to improve access to appropriate healthcare. Before AI applications are used in healthcare, they have to be "trained" using clinical data or synthetic data. There is a large variety of clinical data, such as demographics, medical notes, physical examinations, and clinical laboratory results. Additionally, using the advanced analytics, machine learning, and artificial intelligence techniques that have emerged, there are numerous possibilities for transforming this data into meaningful and actionable results. Despite the wide availability of clinical data, there is a need for more precise and focused data which can be achieved by generating synthetic data.

2.2. AI in Treatment Personalization

The healthcare industry has begun a major transformation with the migration from Health-1.0 (digitized medical records) to Health-2.0 (big data). Medical data is generated and collected from more sources and data are accumulated at higher speed than ever before. Numerous initiatives have been funded globally to efficiently store this wealth of data in a structured manner and apply powerful digital technologies such as artificial intelligence (AI) to analyze and extract knowledge from it. The promise of this wealth of new data is that better algorithms can be produced and patient stratification can be achieved faster, cheaper, and with higher confidence than before. This resulting new knowledge will enable predictive and preventive approaches to health, disease, assay, and medical resource that far exceed the current level. Along this promising path where big data and AI are perceived to synergistically change everything in healthcare, a comprehensive and realistic picture of how this convergence is going to happen is nevertheless absent.

Many are reluctant to simply embrace this convergence again highlighting the previously attempted and often failed examples that shown the impossible-to-replicate nature of healthcare and medicine. There is a subtle but important difference however between what happened in the past and the present situation: the explosion of data. A simple timetable could produce a paradigm shift where the last 60 years (Health 1.0) is followed by a rapid transition to a new age of knowledge generation (health 2.0) that takes decades in traditional industries/classes. The "future" of healthcare as a highly developed science-based industry is plausible in the near future (Health-3.0) since all the ingredients for this development have already been there (data + ambitious/smart/reasonable regulators + massively parallel algorithms). From health-3.0 to the envisioned health-4.0 (where every aspect of healthcare has become personalized and zero-non-value added services are digitalized), additional fundamental research breakthroughs will be required. The service- and destination-based view of how to realize the boom in personal medicine, portrays the roadmap for big data and AI to arrive at predictive and preventive strategies and services in healthcare turned now into big data driven surveillance and optimization of life-style.

3. Understanding Big Data in Healthcare

The last decade has seen rapid advancements in the integration of information technology in healthcare. The emergence of wireless remote health monitoring devices such as wearables and biosensors, proliferation of mobile applications, rise of genomics and proteomics, electronic health records, and advancements in telecommunications have made it possible to collect and store unprecedented amounts of digital information about health and illness. Privacy concerns aside, these data offer enormous potential for transforming the healthcare landscape from reactive disease management to proactive prevention. However, these datasets are also large, complex, and high-dimensional. Even with the rapid development of sophisticated data mining algorithms, large-scale detection of patterns in such data has proven difficult, due to the computational and mathematical complexity of these tasks.

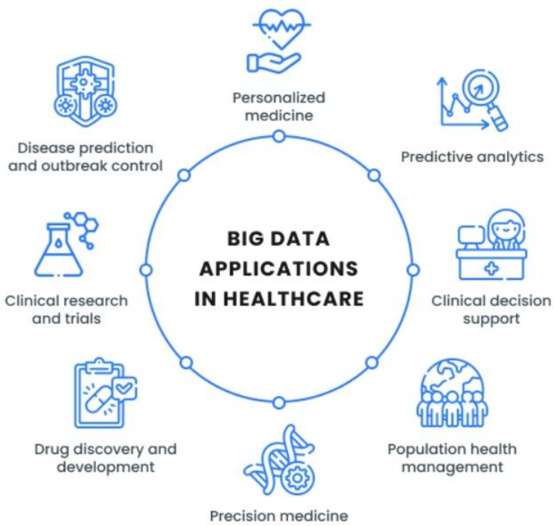

Fig 2: Big data application in healthcare

In the biomedical domain, there is a need for novel and scalable mathematical approaches to understanding these high-dimensional datasets, specification of which has fueled interest in "Big Data". These data offer potential insights into the interrelationships among a variety of molecular factors that influence disease processes, but unfortunately these investigations have been severely limited to date. Hence, in addition to computational developments, mathematical approaches are required to effectively process these data and pose the associated statistical challenges. It reflects on approaches that are likely to play key roles in specifying system-level models of cellular processes such as genome sequencing and mass spectrometry.

Electronic health records (EHR) are digital records of patient medical history and surrounding information that are typically stored on the cloud. They are the by-product of joint efforts by hospitals to adopt a standardized system of record-keeping. In recent years, there has been a general acknowledgment of EHRs as the Big Data of healthcare. Why this is the case is now clear: (1) large amounts of EHRs are generated and managed daily; (2) the previously unlinked, unstructured nature of EHRs makes it difficult to process them using traditional approaches; and (3) a wide array of potentially informative covariates is captured by these records. EHRs have generated enormous interest among epidemiologists, biostatisticians, machine learning scientists, and trend analysis researchers. These records naturally span different domains of investigation, is heterogeneous, often of varying quality, and demand algorithms that can handle all these factors collectively. Importantly, EHRs are evolving—patient data that were at one point dedicated to just storing charts are being refined by clinicians to compile more informative details on patient needs as well as to assist clinicians in diagnosis and response prediction.

3.1. Types of Healthcare Data

There is a large variety in clinical data. This data can be classified as structured, semi-structured, or unstructured, depending on how the data is generated and its storage format. Some examples of commonly used clinical datasets include demographic attributes (e.g. age, gender, cardiovascular risk factors), medical notes (e.g. free-text notes from cardiologists), continuous variables (e.g. EKG curves containing heart activity), physical examinations (e.g. systolic/diastolic blood pressure), clinical laboratory results (e.g. CK-MB biomarker), and image processing results (e.g. cardiac motion vector images and various imaging catheters). Recent advances in big data technologies enable the management and analysis of different types of healthcare data such as clinical data, biomedical literature, gene expression data, and imaging data.

Healthcare stakeholders stand to benefit from AI and big data analytics. Most healthcare sectors employed analytical techniques to harness the power of big data for analyzing historical data, predicting future outcomes, and determining the best action for the current situation. Nevertheless, there is a need for more precise and focused data because a large amount of clinical data is not necessarily superior to a smaller data set. Synthetic data are increasingly being considered invaluable when real-world data does not meet specific needs. For example, when there is no blood glucose data for a diabetic patient, synthetic blood glucose data can be created based on the non-synthetic information. Synthetic data have been well-studied in many domains such as video games and traffic, but not in healthcare data. Data generated and ingested by low-cost and low-power wearable sensors and devices can enhance several aspects of healthcare. Hence, there is a need to bridge the divide between machine learning researchers and healthcare experts.

3.2. Challenges of Big Data in Healthcare

Despite the promise that Big Data in healthcare has to offer, there are numerous challenges that remain to its increased application in clinical pathology. While the continuous probe of cheaper data storage solutions allows for incremental improvements to an already installed data infrastructure in major metropolitan hospitals and networks, the deluge of unstructured data continues to provide no rigorous data management paradigm to follow. The prospects of a parsed out narrative being transformed into well structured, easy to query databases are limited, if not naïve. Efforts on data standardization must first be leveraged before reaching even the second echelon of clinical data. The development of OpenNotes is similar to making all notes present freely available to the wider scientific community instead parsing them to extract information as have done. As a result, legal loopholes involving the ownership of data might not find resolution. The data rights of a patient's database is a highly contested area that will take years, if not decades to unpack, opening up a venue for data monopolies to form and data sourcing to abuse in both at home and health and science. Similar challenges exist for technique adoption in smaller facilities.

Equation 1: Data Volume Growth Rate (DVG)

$$DVG = \frac{D_t - D_{t-1}}{D_{t-1}} \times 100$$

- D_t: Total data volume at time t
- D_{t-1}: Data volume at previous time
- High DVG requires scalable storage and processing systems

An ambitious, yet entirely rated as unrealistic timeline and performance criteria, which the financing of such projects typically depends on, casts the evaluation of technically and socially complex change processes in a very narrow light. For institutions already short on human resources and often trained staff, such a proposition to make such a caliber of personnel instantly available and in a specific manner and burden of heavy regulation and compliance might result in a burden too immense to consider even when these institutions perceive the opportunity. Meanwhile, with already lagging adoption of key technological infrastructures, more ethically sound options such as sought after vendors of these technologies might surmount caution with far less regard for health safety and ethics as care becomes an assembly line in cheaper to maintain but scandal prone institutions.

4. Integrating AI with Big Data

Integrating artificial intelligence (AI) with big data is rapidly growing as a viable, transformative approach to revolutionizing healthcare delivery and clinical decision making. This paper presents opportunities, challenges, and case studies describing scalable, culturally adaptable solutions and relevant evidence of successful implementations. Emerging trends in digital health and medicine with reference to AI and big data analytics (BDA) applications are outlined first. Subsequently, a two-step framework to scale AI and BDA solutions in culturally diverse healthcare systems is presented. Case studies of successful implementation in Singapore's national healthcare, clinical genetics, and public and personalized healthcare systems of India are shared, and results of deeper dives are provided. The paper concludes with a discussion of future research needs, including the applicability of the framework and implementations in other healthcare systems.

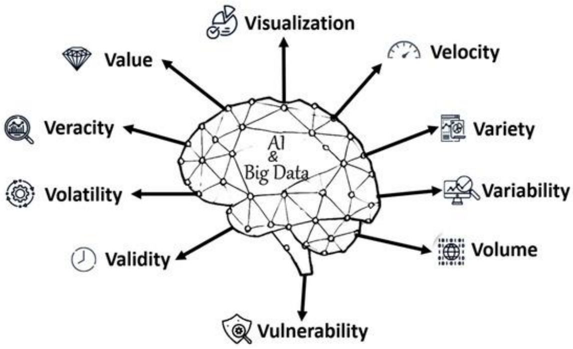

Fig 3: The AI-Powered Evolution of Big Data

Mismeasurement of common conditions or disease risk due to sparse testing; misinterpretation of results from wearable devices; missed infectious disease outbreaks with oversized public health impact; insufficient clinical research account with large implicit costs; and inadequate support of a growing ageing population are examples of the pressing healthcare needs that exist in many culturally diverse societies. The increasing digitization of healthcare records has prompted a surge in AI research and investments, particularly in BDA algorithms. BDA converts data into actionable information that positively impacts healthcare. The adoption of AI methods in BDA solutions is paramount to leverage the vast quantities of raw big data. Emotionally shunned by many healthcare providers, the insufficient adoption and integration of AI methods with the accumulated BDA capability is frustrating for nascent digital healthcare industries at a time when an “AI spring” appears to be underway elsewhere. Such an AI opportunity deficit calls for rapid remedial action for the urgent benefit of all people on the planet.

4.1. Data Collection and Management

Recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency and improve patient outcomes. The COVID-19 pandemic has highlighted the key issues of improving risk prediction, diagnosis, treatment selection and patient involvement in healthcare. In clinical care, AI technologies can aid physicians in diagnosis and treatment selection, risk prediction and stratification, and improving patient and clinician efficiency. Supporting physicians and automating routine tasks can greatly reduce burnout. Yet, most sophisticated AI models exist only in high-profile publications, and only a few models are implemented in clinical practice. The barriers to translating data science research into patient care are inadequate data quality, scarce resources, and high patient confidentiality needs.

Equation 2: Data Collection Rate (DCR)

$$DCR = \frac{D_{collected}}{T}$$

- $D_{collected}$: Amount of data collected (e.g., in GB or records)
- T: Time duration
- Helps optimize system bandwidth and sensor throughput

With the Health Information Technology for Economic and Clinical Health Act of 2009, many institutions have transitioned to electronic medical records that provide a rich medical data source. The healthcare data landscape consists of rich but volatile datasets that stem from a variety of heterogeneous sources, e.g., EHR systems, imaging devices, and patient-administered wearables. These sources store large amounts of diverse data types at a time and space that is highly relevant to patient safety and wellbeing. The discoveries of insights from such data are opportunities for better patient outcomes. However, the analyst side of the pipeline is resource-heavy and time-consuming. Moreover, the high requirements for patient safety, confidentiality, and ethics impede the effective sharing and utilization of healthcare data. Therefore, the prospect of a harmonized ecosystem for efficient data collection and modeling of Healthcare Big Data remains a challenging task.

4.2. Data Analytics Techniques

Descriptive data analytics techniques allow for describing the data and discovering meaningful patterns from it. Whereas explorative data visualization techniques create an interactive environment for visual discovery, visual analytics blends data visualization and data mining, hence combining human ingenuity and machine expertise. Using visual analytics, the understanding of data can be dramatically advanced since analysts are excluded from the traditional bottleneck and are empowered to explore all levels of detail and their interrelations. These techniques can be complemented with supervised approaches such as classification. For instance, combined models are developed as ensemble techniques that combine a growing collection of base classifiers whose predictions are appropriately aggregated. The established methods for constructing base classifiers rely either on data partition or on a problem clustering strategy, hence adding diversity across the different models. They devise a framework to develop an ensemble-specific data partitioning technique using a division bound on misclassification rates of voting classifiers to select from the initial fuzzy partition. They apply the method to conclude on a static partition for synthesized and real medical datasets. Compared to the result of the commonly used strategy, the voting ensemble improves predictions across the whole domain. Classification rule extraction models assist a better understanding of the inferred models and offer the possibility of improving the overall average prediction performance.

Once the target to be predicted is identified, techniques for representing it need to be selected. Standard approaches for time-to-event characterization include the implicit or explicit representation of event occurrence times. In direct event-to-event forecasting domains, either state-event or cumulative count per event type representation is appropriate. For inference on the predictive performance of a model, standard techniques are used to assess the match between outputs and truth. They assess the coverage and sharpness of predictions through prediction interval banking designed for time series and probabilistic forecasts.

Better modeled count-based representations permit capturing higher-order dynamics in event sequences compared to baseline prediction approaches. Count-based representations are constructed to measure the temporal evolution of events of a type in a time window and predict the future by iterating counts transformed through a recurrent neural architecture. Preserving and replicating dataset characteristics when simulating data is a significant challenge for healthcare data anonymization methods. Fulfilling this challenge enables testing machine learning models which pose concerns on data sharing and biases inherent in practical applications.

5. Personalized Medicine: An Overview

Developments in health care are helping to move on from traditional bias symptom-driven medical practice of medicine to one based on a better understanding of disease processes, with increased ability to analyze the wealth of patient information accumulated over the years to help monitor and distinguish between sick and relatively healthy people. Along with better understanding of biological indicators signaling shifts in health are needed to better address wider population at risk, hence the broader concept of population medicine. Recently it is believed that most of the constraints have either been minimized or close to obsolescence since the explosion of alternative ‘big data’ sources of human behavior and the rapid advancement of technologies. Therefore, it is time to revisit this old dream with renewed focused.

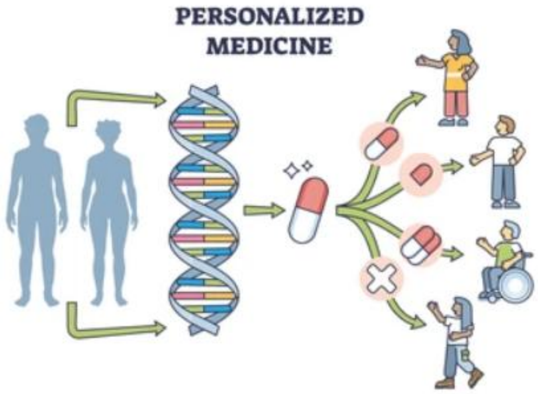

Fig 4: Personalized Medicine

Risk assessment and disease screening are among the earliest applications of computing that have mostly fallen in the realm of descriptive population medicine. The mandated management and reporting of either clinical or laboratory information has led to the construction of vast electronic health record or laboratory record databases, which could be explored to aid clinical diagnosis and treatment decision. To complement existing state-of-the-art evidence-based population medicine services that rely on the advanced literate science of medicine, tools are needed to access, analyze, and manage these vast heterogeneous databases of patient information in near real-time environment to aid timely clinical decisions for earlier intervention. With these digital technologies, the above described vision of big data-centric precision medicine is proposed, which involves the relevant technologies, method, and key research areas to realize it based on the continuous revelation of knowledge and discovery of personalized patient diagnostic and prognostic models and patterns using this staging data-driven approach.

While detailed methodologies for personal modeling, knowledge acquisition, and understanding discovery using clinical, laboratory, and surrounding patient data in big size across multiple sources and vertical disciplines are still under active research, there are abundant academic and commercial initiatives in building real-world health care and precision medicine systems or platforms, which could be reviewed to advance academic solutions in paving the way for this new data-centric era of discovery in health care.

5.1. Definition and Importance

In the biomedical and healthcare sectors, improving diagnosis, treatment, and overall operational efficiency has become vital. Healthcare data is generated daily from various sources, including hospitals, research labs, and home monitoring devices. Still, traditional methods fail to effectively analyze the rapidly increasing volume of heterogeneous data, showing the need for automated systems that can utilize such data for better decision-making. AI is a groundbreaking technology that performs various cognitive functions independently. Big data addresses the challenge of managing massive amounts of information, including complex, dynamic, and diverse data structures. The convergence of AI and big data is considered crucial for optimizing health services and promoting personalized medicine. AI techniques can provide a more comprehensive understanding of medical data, revealing important features in computational predictive modeling, identification of disease pathways, and treatment. To address this, we present a scalable approach to integrating AI and big data in healthcare, an integrated AI engine that extends the big data toolkit with various AI modelling tools, over a general cloud environment that can integrate heterogeneous data sources and move computing resources closer to data sources. It can effectively accommodate massive real-time processing.

Personalized medicine has emerged as a powerful development in the medical care sector, allowing interventions based on individuals' needs, biology, and genes. It has the potential to improve traditional medicine by intercepting interventions earlier than the manifestation of symptoms with advanced diagnostics. Timely intervention using tailored treatment can improve treatment efficacy and reduce adverse effects and costs. Opportunities exist to integrate automated computer systems to assist physicians in making better treatment recommendations, thus improving treatment outcome. Integrated analysis of the correlation between patients' characteristics and treatment outcomes has proven effective in chronic disease management and quality improvement. However, straightforward analysis of patients' traits and treatment history is insufficient for understanding the optimal treatment.

5.2. Current Trends in Personalized Medicine

Personalized Medicine is an emerging trend in medicine allowing tailored therapies for every patient based on personal specifics to increase therapeutic efficacy and effectiveness while decreasing side effects. While personalized medicine has already been a trend in fields such as oncology, it is expected to permeate through any medical field with the implementation of Artificial Intelligence (AI) platforms enabling personalized care and individualized therapies based on complex patient interactions with the overall healthcare ecosystem. AI is expected to countermeasure existing system deficiencies by finding distinctive patient patterns commonplace in real world by analyzing diverse and vast amounts of data. AI has the potential to radically redefine the future of healthcare while granting a centralized framework for healthcare delivery irrespective of its mode.

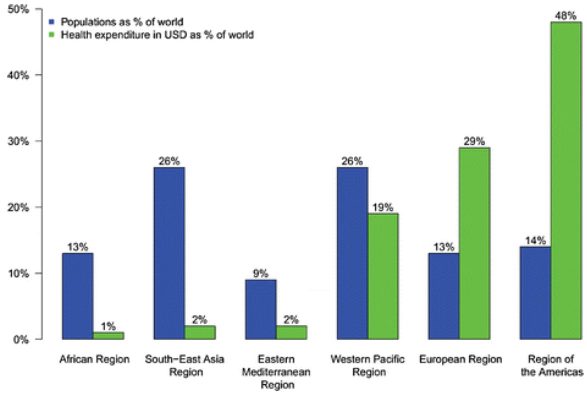

Fig: From big data analysis to personalized medicine for all: challenges and opportunities

Current healthcare systems are comprised of nearly a dozen islands functioning separately, having little to no integration of resources or data between them. Human and ecosystem factors underlying healthcare are so convoluted that the live functioning of the healthcare ecosystem in terms of patient journeys traversing through the system is beyond judgement. The descriptive analysis of patient journeys deepening chances in health outcomes revolving around healthcare utilization, treatment adjustments, or other patient-centric factors is an unsaturated area in healthcare literature. Understanding and visualizing patient journeys is vital in the assessment of care quality complementary to conventional statistics involving cohort type analysis.

6. Case Studies in AI and Big Data Applications

Vandenberk et al. describe how numerous digital health applications, where information and communication technologies are employed to manage illnesses, prevent complications, and promote wellness, have emerged. Some of these applications include wearable devices, mobile health or apps, telehealth in cardiology, and telemedicine. The first category includes devices that monitor heart rate, activity, cardiovascular rhythms, arterial stiffness/pressure, and others. Various apps have emerged to prevent CV risks, motivate exercising, and promote lifestyle changes. These technologies are promising as existing evidence indicates that they can improve access to healthcare and lead to a more personalized healthcare approach by incorporating patient data to tailor preemptive actions, therapy choices, and treatment objectives.

Fig 5: Exploring the Intersection of Big Data and AI

Evidence-based medicine applications train AI applications in healthcare on clinical data, simulated datasets, or on a mix of both. Digital data in healthcare can be heterogeneous in a large variety of domains, such as demographics, medical notes, clinical laboratory results, medications, allergies, and others. Data analytics has become broadly used in healthcare with a variety of advanced analytics, machine learning, and AI techniques that may deliver meaningful results. The healthcare stakeholders can apply analytic techniques to analyze historical data, predict what is going to happen in the future, and estimate the best action to take concerning the current situation, based on experience from the past.
Despite the broad availability of clinical data, needs remain for more precise/focused data regarding certain objectives, diseases, or conditions. Synthetic data refer to data that are generated to meet a specific need. Data generation of synthetic, behavior-based sensor data is critical for validating machine learning techniques that could be applied in healthcare. Available approaches to generate synthetic data to satisfy analytical modalities are almost equally broad, but many are limited in complexity. A preferred methodological approach consists of using hidden Markov models, regression models, or a mixture of both, initially trained on real datasets to finally generate synthetic time series data. Time series distance measures are additionally computed to quantitatively assess the realism of the synthetic data. In a more broad sense, synthetic data generation methods have shown sufficient reliability for being used in real-world ML applications.

6.1. AI in Oncology

Oncology is a data-rich field driven by a variety of aspects emerging throughout the journey of cancer care, including the heterogenous nature of tumors, increasing use of multimodal datasets, and growing digital trace data of patients. Artificial intelligence (AI) has been increasingly applied to analyze the vast amount of data generated in oncology. Traditionally, oncologists reviewing a scan on CTs, MRIs, PETs, and X-rays relied on experience. In the era of enhanced predictive analytic models through machine learning techniques, deep learning methods enabling automatic tumor detection and segmentation have recently gained interest. Significant accuracy improvement and diagnostic yield has been achieved, allowing timely treatment initiation or emergence of enhanced post-therapy monitoring frameworks assessing tumor growth or response. Nevertheless, their rollout to clinical practice remains cumbersome owing to key challenges. These include concerns on safety, robustness, and validity, as well as opacity and model interpretability leading to trust loss. Moreover, as AI solutions are being used in highly consequential aspects of patient care, the legal liability surrounding erroneous or non-robust models needs to be clarified.
Radiomics extracting quantitative textural features from medical imaging or pathology has also been a great research focus in oncology. From well-established textural features, significant advancement on using novel deep learning-based approaches for radiomic extraction and prognosis modeling has been achieved. However, many obstacles remain on the path to clinical implementation. Symptomatic of these challenges, only limited prospects for the use of AI solutions in pathology or genomics have been marketed. AI tools encoding great technical novelty and accuracy with extensive peer-reviewed evidence are readily available for commercialization, but only a few of pursued AI models have launched in-house for oncology issues. These considerations feed into the discussion on the required technical and regulatory advancements to broaden the clinical implementability of beneficial AI.

6.2. AI in Chronic Disease Management

Chronic diseases are an increasing concern for the global healthcare system. These diseases, e.g. hypertension and diabetes, seriously threaten human health and affect the ability of individuals to work. Although wearable devices have helped to control chronic diseases, large-scale data still mainly stay at local data centers, affecting the quality of deep learning training. Therefore, chronic disease health management systems that offer real-time monitoring and smart recommendations need to be developed.

Equation 3: Logistic Regression for Disease Prediction

$$P(y=1|X) = \frac{1}{1+e^{-(\beta_0+\sum_{i=1}^{n}\beta_i x_i)}}$$

- $y=1$: Positive outcome (e.g., presence of disease)
- x_i: Input features (e.g., age, blood pressure, glucose levels)
- β_i: Learned coefficients from training data
- Common in predicting diabetes, heart disease, etc.

The combination of AI, blockchain, and wearable technology helps realize personal health monitoring, decentralized data storage and sharing, and knowledge extraction of cardiologists. Based on these technologies, a deep learning-based smart healthcare system is proposed, supporting a wearable device for chronic disease monitoring, a service ledger for data sharing and privacy protection, and a knowledge base for smart recommendation. In the healthcare industry, emerging applications of AI mainly include big data mining, rule engines, and deep learning. Big data mining could extract associations among data to retrieve health management models for chronic disease diagnosis. A rule engine could execute business-related rules including rules based on expert knowledge to make decisions on a patient’s health status. Deep learning could construct a multi-layer complex structure for processing multimodal data to form a more abstract representation of a patient’s healthcare data for diagnosis . The healthcare industry also faces challenges such as chronic disease data explosive growth, rapid development of AI-based services, and compliance with regulations for AI knowledge management in healthcare. With the development of wearable devices, mobile apps, and electronic health records (EHR), chronic diseases health reports, lifestyle activity records, and biometric data are generated, forming a new big data era. To avoid conducting harm to patients, AI systems must be trustworthy, and knowledge sharing among regulators and governing bodies is essential.

7. Ethical Considerations

Policies involving the AI (Artificial Intelligence) and Big Data-enhanced healthcare ecosystems may unveil new potentials triggering significant ethical implications. Notably, emerging health and technology laws, such as regulations governing AI in medical devices, may shift traditional paradigms of personal injury lawsuits by holding other parties liable, such as the software developers and the data brokers in addition to healthcare professionals. Thus, it is important to discern how and to what extent these laws will shape epidemiological data regulation. Although AI and Big Data technologies may make it easy to identify high-risk subjects and will alleviate physicians’ efforts and cognitive burdens to monitor chronic diseases, it is crucial to have transparent explanations for public health decision-making processes that distinguish legitimate public health policies from unethical surveillance measures, as memories of previous surveillance cases remain in public consciousness. The legal and ethical challenges brought by AI and Big Data-enhanced health technologies require securing equitable compensation schemes for those harmed, re-establishing shared accountability mechanisms based on ethical codes of conduct, and efficient oversight to ensure compliance. Needed long-run solutions are expected to be devised collaboratively by multiple stakeholders including governments, industries, and academia.

The convergence and mutual reinforcement of digital health technologies trigger wide-ranging questions in law, regulation and governance. In particular, it is necessary to understand how and to what extent the enactment of laws governing the use of AI and Big Data is changing established rules concerning health data. Increased scrutiny has been devised in terms of policy and decision-making processes of health and technology data. COVID-19 has vastly accelerated data collection, saving lives. Also, the regulations proposed by the European Commission massively expand personal data regulation with huge implications for health data. AI and Big Data technologies combined under health and technology ecosystems are collecting unprecedentedly large individuals’ health data and capabilities to scrutinize through them. However, technologies that are becoming more complex often raise ethical and legal concerns. Thus, it is timely and essential to carefully analyze new resultant size, scale, depth, and trust factors of issues that health and technology raise. In doing so, emerging regulations governing the AI and Big Data aspects of health data are used as lens through which to scrutinize what new ethical, legal or regulatory perspectives emerge or arise and how. Decisions on such questions will shape future social structures.

7.1. Data Privacy and Security

AI-based health services are often provided through monitoring platforms managed by third-party health analytics teams, also known as model producers. These services can detect deviations from patients' healthy states and suggest preventive measures. However, it is both urgent and challenging to protect patients' privacy against exposure or leakage of sensitive health information. Those breaches can violate privacy regulations and incur patient social, economic, and health risks. Under these circumstances, healthcare teams, researchers, and model consumers usually require privileged access to patients' shared data to detect chronic disease development and enable wellness assessment, population-based modeling, risk factor identification, and predictive modeling.

Though many analytics schemes have been proposed, preserving data privacy in healthcare without impairing the data utility is a great challenge. In the ideal case, both the data held locally by patients' personal devices and the models reused by those teams should be fully protected against either direct or indirect exposure outside the personal devices. Moreover, it is necessary to sustain the privacy requirements during the phases of data storage, processing, and communication. Therefore, the ideal privacy situation is almost impossible as it is infeasible to hide both patients' private data and model consumers' construction algorithms against all kinds of attempts. An ideal design of privacy-preserving deep learning frameworks is to hide data and model information and still ensure effective training, inference, and continual learning on deep learning or hybrid models. Still, too complex and super-secure encryption schemes jeopardize almost all computations and services; meanwhile, simpler schemes, such as only anonymizing shared data, are inadequate against attempts to infer private information over the access results.

Different privacy-protecting methods impose distinct requirements and limits on the architecture and development of privacy-preserving analytics. An insufficiently designed analytics framework would be exposed to potential leakage of shared data. Even with well-designed schemes, the architecture or designs of analytics algorithms would become much more complicated with limited processing operations on obfuscated data. On the implementation end, these privacy-prescribing frameworks would incur increased costs for storage, transmission, and computation.

7.2. Bias in AI Algorithms

Algorithmic bias may result in differential performance across population groups in AI algorithms, typically related to race, ethnicity, sex, age, and neighborhood. AI algorithms, by design, are tuned to deliver better performance on specific population groups that are better represented in the training dataset. In this sense, these group-specific performances follow a fairness tension—automated systems gain performance at the expense of fairness invariably when the deployment data has significant population shifts relative to the training data. Biases in the predictive outputs often become apparent only after deployment of the algorithm, with the consequence of not being caught early during development. A problematic AI algorithm that is well-calibrated on a subpopulation with high-volume and rich historic data could deviate dramatically from its intended purpose on communities with scant data history, resulting in the so-called "black-box" models with opaque and unreachable high dimensional abstraction for each prediction. Moreover, harmful bias, e.g., bias against psychiatric patients, is extremely challenging to detect because predictions that are highly skewed to the affirmative class persistently make right decisions from the point of complete loss of merit metrics.

AI fairness is difficult to create, achieve, and maintain globally in practice. It is a challenging task to define the "fairness" of AI algorithms in a coherent and precise manner since fairness measures are often task and context-dependent definitions. AI fairness is an ongoing process that relies on dynamically developing good definitions, measures, and techniques. The inconsistency in operational definitions of fairness "parse" into two issues: the input data parity (fair representations) and the algorithm distributional parity (fair decisions). Post-processing fairness techniques start from the predictive output of the model. These techniques often perturb the original outputs of the model to reduce the sensitivity to certain sensitive variables of the original output. AI fairness is probably best practiced locally—and thus, debiasing or bias mitigation can only be solved and addressed well on a case-directed basis.

8. Regulatory Framework

The new era of Big Data is associated with important opportunities, but at the same time with challenges that need to be thoroughly addressed. Market-oriented players are constantly proposing new products and services based on AI technologies, and this is more and more evident in the healthcare domain, where digital health tools based on AI are promising to change the way in which health is assessed, promoted, and safeguarded. AI technologies have proven potential to enhance the current healthcare ecosystem, optimizing the workflow, improving the diagnosis process and the accuracy of diseases prediction, increasing patient safety and security, facilitating personalized medicine. On the other hand, along with the promise of an affordable and more efficient treatment comes the unsolved question of legality. Decentralized healthcare systems pose ethical concerns regarding data ownership, accountability, and privacy. Furthermore, quickly evolving tools and technologies often remain out of regulatory applications and supervision, raising doubts concerning inequalities in access to state-of-the-art treatments and methods for the most vulnerable groups. These anticipated benefits, that sometimes are more like a wish, propagate a heated discussion for research and law-making, leaving much effort to the regulatory and managerial framework in which AI technologies interact with healthcare. AI-based technologies have the ability to assure unprecedented tools able to substantially change the healthcare domain. However, this is mostly a wish rather than a reality. The pace of technology evolution is indeed adversely affecting the time of implementation within the regulated healthcare domain. In the past two decades, healthcare has radically been changed by the introduction of artificial intelligence and the use of machine learning algorithms. With this change, the healthcare domain evolution came into a phase '2010' where regulations, national laws, and guidance documents were inadequate in dealing with such powerful and potentially dangerous technologies. The technology development within the Healthcare and Life Sciences regulation is more influenced and triggered by daily stories on privacy breaches and trust issues than by proven assistance to the healthcare domain. On the other hand, a need and challenge of a rigorous evaluation framework are raised to accompany the technical development of AI and ML algorithms. In 2018, the artificial intelligence exertion within the health domain is defined as a regulation-free Wild West.

8.1. Current Regulations in Healthcare AI

The rapid integration of Artificial Intelligence (AI) applications into healthcare has been accompanied by a proliferation of ethical and regulatory concerns. This narrative review critically explores the landscapes of current regulations for AI in healthcare, regulatory issues not yet tackled, and emerging ideas concerning the need for regulations more tailored to healthcare AI. For decades, advances in computing and sensing technology have led to the development and proliferation of digital technologies capable of gathering massive amounts of data and processing it to extract meaningful information for assessing health or tracking the individualized progress of a prescribed therapeutic regimen. Digital technologies find application in several fields of healthcare, including pharmaceutical, biomedical, and consumer health. Healthcare technologies, together with the vast availability of medical data, and the unprecedented advancement of computational intelligence, led to the rise of AI-based tools capable of optimizing clinical workflows to enhance patient safety and support clinicians in the diagnosis of diseases and in the customized treatment of a patient. Several cutting-edge AI technologies are being incorporated into healthcare, positively impacting it, and achieving considerable successes in almost all medical fields. For example, smart learning systems have been developed to diagnosis skin diseases based on skin images, achieving remarkable accuracy and surpassing previous methodologies. Machine learning-based models have been devised for predicting the spread of breast cancer, achieving high accuracy and assisting doctors in precise analysis. In the ongoing combat against COVID-19, different types of unique models for timely identification of the disease from CT scans and X-rays have been proposed and were proven to be high-accuracy solutions. Likewise, technology has improved the accuracy of cancer imaging, providing valuable insights to doctors.

At the same time, the exponentially large and complex growth of data available in the healthcare domain is reshaping the landscape of security and privacy in healthcare. Robust security upgrades are crucial to guarantee the safe handling of vast datasets produced and gathered by hospitals and electronic monitoring devices. These achievements notwithstanding, many challenges still emerge for the ethical and regulatory issues of AI in healthcare that are addressed in this work. The use of AI technologies presents ethical issues, which may surface as concerns related to their implications for healthcare professionalism, for patient or public rights and interests, for equity and unfair discrimination, for accountability, or for privacy and security. The increasing use of AI technologies in healthcare is changing the healthcare landscape in ways that have ethical implications. AI in healthcare also raises questions of public and policy interest regarding misuse, fairness, inequity, discrimination, bias, and social justice. A review identifies and characterizes the ethical issues that arise with respect to AI in healthcare. Based on these characterizations, the implications for the health professions are also discussed, including the need for continuing education, training, and the professional role in informing relevant policies. AI technologies are revolutionizing healthcare and medical research, with significant promise to improve health outcomes and healthcare processes. Large amounts of varied healthcare-related data can be curated, processed, and analyzed to generate novel insights and knowledge. AI tools can efficiently and automatically sift through disparate and unstructured data sources to extract previously obscured datasets. AI technologies can also facilitate drug repurposing. Not all AI implementations are of high quality. Errors or flaws in the algorithms or poor-quality input data may result in an inaccurate analysis or prediction.

8.2. Future Directions for Policy

While economies everywhere are becoming increasingly driven by data, the digitalisation of health services is experiencing an unprecedented increase in scale and intensity due to the COVID-19 pandemic. Regulations promoting the free flow of personal data across countries and introducing strict safeguards for the use of this data have just been recently enacted. National initiatives for national health data and AI strategies are being rolled out at the same time worldwide, which has steered international attention towards the immense potential of data science in health and healthcare. With the prospect of new jobs, products, value chains, and business models, the digital health revolution weighs heavily in public debates.

They note, however, that with the excitement comes apprehension. The stakeholder landscape is radically transformed with the rise of big data and AI in Europe. In addition to government actors and the medical community, other stakeholders, such as big tech, data service providers, the insurance industry, and patient/family advocacy groups, are also significantly fuelling the debate on transformed health data governance. Existing governing structures and associated policies, including ethics and regulation, have proven to be ill equipped. Existing initiatives lack clarity regarding the substantive conditions of use of health data. European efforts are further complicated by increasing geopolitical tensions. Solutions designed in one technological world are either incoherent or ineffective if they endeavour to be implemented elsewhere. There are increasing concerns over overreach by governments in data governance regarding health data, especially in the wake of the pandemic.

It is concluded that these settings account for urgent follow-up questions and preparatory tasks. No stakeholder alone will be able to address the intricacies of these tasks. Promoting the health data revolution depends, more than ever, on collective underpinnings and collective responses by all stakeholders. Immediate cleaning up of the mess left by the pandemic regarding oversight and regulation of health data can only be pursued through elaborate public-private partnerships. Prior to the horizon of data-driven health research envisioned a decade ahead, the emergence of data infrastructures will continue to challenge incumbents. The unprecedented scale and intensity of these efforts generate teachable moments regarding what ‘real’ governance means. Inter-mediation at the governance level between science, market, and state actors remains paramount to avoid dystopian scenarios.

9. Scalability of AI and Big Data Solutions

As most healthcare AI systems rely on big data interfaces to aggregate data from numerous sources, several standards are being discussed. The optimal architecture and data standards are a hotly debated topic. A situation where data from hospitals of differing architecture cannot be integrated and processed would not be scalable or appropriate. Uniformity in this aspect should be prioritized. Suppose information regarding a diagnosis is encoded in a natural language problem description in a legacy system, while a more contemporary formalized one allows for accurate diagnosis prediction based on lab readings and age. Due to discrepancies in problem description and information storage structure, a careful data transformation and legacy data diminishment may be necessary. There is always the danger that data may be interpreted in unintended ways or left behind. For example, algorithms can work against early detection efforts if early stage disease data is misclassified as onset or terminal data. It would be a reasonable requirement to have the original data archived and transmissible along with any analysis results and the respective chain of interpretation and modification. Potential applications of big data and AI to stratify the medication response, treatment benefit, and disease risk in genomic studies can be complex. Availability and price are likely to become significant factors in determining the standard for software specifications. The new question is how often and under what circumstances one big data and AI implementation works for another. Can data and a model, for example, created for one hospital be applied to a different one? Scrubbing and generalizing the model sounds well. However, treatment efficacy and side effects may depend on patient and provider homeostatic self-adjustments to trends, alongside shifting recruitment schemes or procedures adopted for trial data generation. For another instance, on treatment-change identification, numerous natural resources, feedback, retrospection, and reconsidering providing solutions have been put to work by huge universities or corporations. Without a doubt, this question is among the most important challenges of big data and program development in the health service. How does one determine that the scope comes close enough to real-world practice? The question should also be supplemented with adjoining interrogations; e.g. does provision always concentrate on clinical mitigation?

9.1. Infrastructure Requirements

Most patients expect that advances in data science technologies, including artificial intelligence (AI), will soon be used to help with clinical decision-making. This will only be feasible if a massive data infrastructure can be developed that scales to accommodate the size of the current and future datasets, and access to this infrastructure is made available to researchers and clinicians. As in other industries, such as finance and social media analysis, the use of standardized stacks of hardware and software will be necessary to enable and accelerate the work of clinical AI researchers with heterogeneous and expansive data. The design of such infrastructure will require careful consideration of both clinical data sources and machine learning and data science development processes.

The rapid digital transformation of the healthcare industry has fueled an increase in the amount of healthcare data generated globally. The US health system collects clinical data from dozens of sources, including the millions of visits and procedures every week, public health information submitted to state and national registries, and myriad other technology, device, and lab data streams. To fully realize the potential of this information, an integrated and transformative approach to data storage, management, and analysis must be developed. Integrating large, complex, heterogeneous data sources from diverse technology vendors can take months to years, and even thereafter, only limited insights are found relative to the size of the data and amount of effort. AI and advanced analytics, which rely on large amounts of data, could offer new opportunities to leverage these extensive resources, but the data ingestion and pipeline infrastructure necessary to make this feasible do not typically exist. Developing a healthcare data science platform that supports integrated storage, management, and analysis of diverse data types is necessary to create insights that improve patients' care pathways and safety.

9.2. Cost Implications

Cost implications associated with a big data approach to healthcare originally assumed that efficiencies gained from preventing repeat testing and curtailing unnecessary procedures would offset the costs of the software implementations. This assumption has since proven unwise. CPOE applications are notoriously expensive to install and maintain, and most hospitals question whether the economy of the investment will ever be seen. The most innovative feature of a scalable big data approach is its widespread dependency on openly available software solutions from the digital community. It is assumed that the providers will bear the costs of the software developments; only the minor fractions of the costs ongoing maintenance will be centered within the healthcare sphere. This relatively inexpensive approach benefits from the enormous recent investments in storage and computation power. In parsing the cost implications of this new approach, it must be acknowledged that implementations based on closed, proprietary software are less expensive than those based on open source software. Additionally, higher implementation operating appeal factors in within the overall calculations of lifetime costs. Governments of countries such as Finland and France understand the utility of a big data centered approach to healthcare and have initiated large-scale activities. Their further diligence in crafting regulations to control censorship of data and access to care will ensure sustained innovation. With more and novel applications coming to fruition, more health data generated daily and framing the ability for personalized medicine, it is hoped that in the near future the cost effectiveness of a scalable, big data approach to healthcare will manifest and appropriately influence care for the whole population.

10. Future Trends in AI and Big Data in Healthcare

Organizations across sectors are investing heavily in machine learning (ML) technologies, which promise to enhance operational efficiency, increase profitability, and create greater consumer welfare. There is a race to develop these technologies and acquire talent, as organizations fear that efforts may be set back 10 to 20 years if they fail to act quickly. However, few of these technologies have been feasibly or sustainably deployed at scale. As a result, the confidence and buzz have given way to growing skepticism and pressure for better results and returns. Expectations regarding the resulting economic and social benefits have also come down.

The situation with AI applications in healthcare is reminiscent of the situation with ML in other industries, where many have touted the transformative possibilities of these technologies but where, at present, few systems produce maximum feasible impact. Interest in AI has surged immensely, alongside fervent discussion regarding the promise of these technologies to improve quality, efficiency, and equity in health. Research and investment by private firms, hospitals and health systems, and the government has grown rapidly. A wide variety of AI applications have been proposed to improve health outcomes across sectors. These include new prevention and health promotion initiatives, clinical and pathological decision-support systems, and automated billing and coding systems for health administration and public health.

The race to leverage AI and develop specific applications has been sparked in part by the competitive advantages it may confer. However, it has also been fueled by the expected twin benefits of improved health and lower costs that many applications promise. AI tools have the potential to support everyone at every level of the health system and to increase access to health delivery. AI systems could move healthcare from a top-down, specialist, and hospital-centric model of care to a highly distributed AI-powered patient, family, and population-centric model of care. There is intense interest in these possibilities on all sides of the healthcare enterprise.

10.1. Emerging Technologies

The use of digital technologies to transform medicine through individualized treatments can revolutionize healthcare and well-being. Artificial intelligence is at the heart of this transformation and has been instrumental in deriving engineering solutions to monitor, process, and integrate large volumes of data at the population and individual levels. Tailored treatments derived from AI will assist patients, physicians, and health systems in handling current challenges. Current medical practices generally focus on treating symptoms and ailments for large groups of people. Legacy delivery practices are often incapable of treating the underlying nature of a given condition and have produced a system with erratic quality and unsustainable costs. Advances in genetics, engineering, and computational analyses have improved our understanding of the human body to redefine a path for healthcare. Emerging medical practices are focused on individual complexities that can manipulate disease interventions at the molecular level. DNA sequencing, high-throughput screening, molecular diagnostics, and advanced imaging methods embody some of the signs of progress of these emerging technologies. This new era of modern medicine also produces big data, which requires colossal amounts of integration and analysis that are better suited for digital technologies. Significant research efforts are centered on regenerating diseased or lost tissues and organs, in-depth analyses extending beyond the clinician's limits, and novel trends in disease prevention. This paper explores ways in which digital technologies will support a transition from conventional to personalized medicine. From disease categorization to defining and standardizing biomarkers, wearable devices, sensors, and emerging forms of data are increasingly embedded into ecosystems. Existing samples and data with different conditions of collection are still part of the picture. Practices around samples in pathology are being transformed by digital pathology. Scholars observe a trend of consolidation as virtual biobanks bring together resources from multiple biobanks.

10.2. Predictions for the Next Decade

Data has proven to be the new currency and resources in the digital economy, fueling startups valued in billions or even trillions of dollars by harnessing algorithms to monetize their data. With healthcare becoming increasingly data-driven, there is increased interest in how big data can be utilized to unbundle the patient journey and understand improving prevention strategies, optimizing diagnostics, and developing therapeutics. Though the theories are strong, there are gaps in the process chain, and while a few companies and research institutions are looking to enable data sharing and ask the right questions, many hurdles still need to be resolved, including technological scalability, regulatory guidance, protection against misappropriation, and trust.

Lessons learnt and recommendations for general practice healthcare are discussed concerning big data and the potential pitfalls to avoid. The transition to digital health has just begun and will accelerate with the COVID-19 pandemic and increasing access to new software. The underutilization of investments made since the last wave of investments should be confronted and learning from experience to avoid difficult transitions. EHRs should be modular, improve understanding of the information received and its connectedness by combating cognitive overload, and preventive health checks should be further automated. Wheat and chaff differentiation will become increasingly important as new software surgically adds to the current happening in healthcare.

The knowledge will be generated from the chaff not used; the biggest obstacles prognostic or predictive value from other software are integration, learning from variation, scalability, and safety. Open-source collective learning from variation across practice and national borders; crowd-sourced modelling of the sum of experience, and scalability are needed. Learning from cohorts with and without problems has the power to predict health or deterioration based on the big picture data collected from different domains. Healthcare's biggest chaff problem is misuse, misappropriation, misinterpretation, misunderstanding, and mistrust, asking too much effort from caregivers and too much commotion.

11. Collaboration between Stakeholders

As it stands, few institutions have the necessary infrastructure to design and deploy external collaborative studies on healthcare data, let alone cleansing raw data as needed for analysis. These form twinned bottlenecks preventing AI services from being prototyped and used securely across different organizations with access to relevant data. This solution addresses the states preventing irregularities in AI data analysis activities on healthcare data across certain institutions: an approach that compresses the data acquisition and cleansing activity of organizations while maintaining high security and confidentiality standards on the data. Proof of concepts demonstrate the feasibility of this method. In terms of future work, it would be interesting to test it virtually. Under defense management responsibly, it could be tested on healthcare data obtained from a publicly available dataset.

Advancement of artificial intelligence (AI) platforms that uplift novel systems for computational medicine and facilitate team science will increase patient safety, augment healthcare value, and improve patient outcomes. Recent advances show a heightened interest in healthcare AI, as 42% of healthcare establishments are reportedly seeking solutions regarding leveraging data, analytics, and AI technologies to promote organization-wide digital transformation. On the provider side, AI implementations can be clinical decision support tools that assist physicians in diagnosis and treatment selection, risk prediction and stratification, and operational decision support for improving patient and clinician efficiency. There is a wide array of AI technologies that have been implemented in health settings across several dimensions, mainly focusing on radiology, pathology, and EHR-based solutions. AI validation for deployment includes clinical performance in terms of recall, precision, and other clinical interpretability metrics, development resource efficiency in model training duration and cost of data acquisition.

11.1. Role of Healthcare Providers

There has been a surge in digital health applications where contemporary information and communication technologies are used to manage illnesses, health risks, and to promote wellness. This includes wearable devices, mobile health, telehealth, and telemedicine. This evolution has the promise to improve access to healthcare, reduce inefficiencies and provide a more personalized healthcare. Although various applications are now widely used, most only monitor risks and do not recommend or initiate treatment for any abnormality. This gap could be filled by complementary applications which estimate patient risks with predictive models and use this information to provide offer suited therapies directed by clinical guidelines. Such applications are generally called artificial intelligence -based applications. Before AI applications can be used in healthcare, they must be trained using clinical or synthetic data. Training needs curated clinical data on a specific condition, which only few organizations are able to provide. There is a large variety in clinical data, such as demographics, medical notes, physical examinations, and clinical laboratory results. Along with the emergence of advanced analytics, machine learning, and artificial intelligence techniques, there are numerous possibilities for transforming this data into meaningful and actionable results. Healthcare stakeholders can use analytical techniques to harness the power of data not only for analyzing historical data, but also for predicting future outcomes and determining the best action for the current situation. Enabling insights for better decision-making, organizing care and cost efficiency, and providing personalized care are the potential benefits.

Despite the wide availability of clinical data, there is a need for more precise and focused data which can be achieved by generating synthetic data. Synthetic data refers to any production data applicable to a given situation that is not obtained by direct measurement, but generated to meet specific needs or conditions. This definition thereby includes simulated data generated based on a predefined model or testing data created based on programming criteria. The generation of realistic, synthetic, behavior-based sensor data is a critical step in testing machine learning techniques for healthcare applications. Many existing methods to generate synthetic data are limited in complexity and realism. One of the preferred approaches is to use hidden Markov and regression models that are initially trained on real datasets to generate synthetic time series data composed of nested sequences. Time series distance measures can be used as a baseline to assess how realistic the synthetic data is in comparison to real data. It has been shown that this produces more realistic data when compared to random data generation. Even in the problem of limited available real data, synthetic data methods have shown sufficient reliability to be used in real world machine learning applications. AI can be defined as the ability of a computer to complete tasks in a manner typically associated with a rational human being. Understood as a machine decision maker, AI may be classified as narrow AI (used for a specific purpose) or generalized AI (able to independently reach human-level intelligence).

11.2. Involvement of Tech Companies

Tech companies and partnerships are a very useful mechanism for sourcing the necessary technology infrastructure for the proposed systems. Tech companies are technology providers who may source the relevant data from partnerships. Tech companies frequently are data health suppliers who license them to research institutes or drug companies in return for payment, usually a royalty model. Their willingness to become involved in projects can help build a case for success, they also have a solution development mandate, pointing to what type of solutions can be supplied. Tech companies also have a development capacity, this is useful for building the first prototype systems. Tech companies also are a source of data. It may not be much data at the start, but health data on the population can aggregate over time in health and care settings, allowing projects to become clearer. Tech companies also can contribute against a well-defined algorithm roadmap. It is important that they are not simply partnering to get into healthcare for the first time, as the learning curve can be steep. Secondly, health systems also spend a lot of money ensuring they comply with legislative requirements. Most of this is legislative requirements imposed upon them. Some companies may be willing to participate in providing some of the tools early on that they currently use, as this is both a means of seeds trading and testing also new systems. However, they may become concerned about using technologies that cannot be rolled out in a participant’s health system. There will need to be a parallel stream of systems community capacity building engagements. Tech companies should be linked to health systems’ on-premise systems by a well-tested agreed application programming interface. Finally, there are a number of initiatives aimed to begin to aggregate population health resources and processes. Efforts underway to integrate temperature, health-seeking behaviors, demographics and health care access are examples of those aimed at the health outcomes end of the forecasting concepts. As these become more mature, partners will also start to emerge. Critical to the growth of this pool of aggregated experiences will be the capacity to freely code or utilize the tools built to advance growth. This will be before it reaches prototyped systems or hosted on an on-premise system type situation in par with the actions of the tech companies too.

Finally, coding an emerging success pool will help early on engaging successful partners. Grounding the engagement to a stack is a very appropriate first layer for aggregating knowledge about these systems. Universities are also receptive to an Open and Linked Data Speakers' event where explorations have thought of early lessons and systems built. Training tools can assist this too. The Health-Related Big Data and Artificial Intelligence programs can better understand these agglomerations of tool, resources and process systems.

12. Patient Engagement and Education

Given that education is of utmost importance for effective delivery of personalized medicine, extending the EHR-based interactive patient engagement tools, resources can be developed to engage patients with diverse educational material. A few examples are mentioned hereafter. The media used for patient education can take advantage of the existing templates for the design of educational resources, as publishing tools are now inexpensive ways of communicating health information. The type of resources offered to patients includes educational videos, infographics, curated tweets, or even journal articles. A sophisticated pipeline can be developed to cater the delivery of diverse health information, each catering to a different type of patient need. In this way, patients can be educated on the diagnosis, safety and efficacy of drug therapy, prevention of consequences of illnesses, and at times gain insight into health-related facts from diverse sources not restricted to the medical domain. This is expected to address health literacy effectively, and close the knowledge gap, resulting in a more optimal application of personalized treatment.

Machine learning can play a vital role by capturing and quantifying differences in comprehension. This could include using syntactic and semantic coherence tests and context-free grammar parsers, and delivery of personalized information could be accomplished by decoding comprehension and identifying patients at risk of underwhelming knowledge. To capture compliance, sensor-capturing devices may be used in conjunction with machine learning algorithms. Diverse computational models can be created to reflect the interaction/satisfaction function of the patient, patient targeted health interventions can be extended, and digital phenotyping approaches can be applied to quantify behavioral outcomes at a population scale. Wearable devices are expected to enable remote patient monitoring, and data on heart rate, skin temperature, and sleep patterns are expected to alert patients in case of imminent health events. Here, machine learning has a pivotal role to play through classification algorithms to associate data sequences with health events, and prediction algorithms to classify the risk of future events. Automated pipelines can be implemented to signal alarms of irregularities in heart activity, sleep, and behavior or any deviations from typical patterns with patient-relevant propositions. Automated communication channels can notify the patients of their high-risk status, or the availability of safety and educational resources in cases of non-compliance. EHR-embedded simulations can be run to develop models individualized to each patient, and models can be constantly refined with patient follow-ups.

12.1. Importance of Patient Data

The "Digital" industry has seen complete maturation in its offerings, from hardware to networks to applications. After decades of exponential growth, products and services are now cheap, scalable, ubiquitous, and can be seamlessly integrated across systems. The sectors of retail, media, banking, gaming, commerce, and telecommunications have undergone radical shifts. These sectors attained digitally native status, with the protection of high volume, high velocity, and variety of data. All these developments have brought enormous advances in disease diagnosis and treatments; they have also introduced new challenges as large-scale information becomes increasingly difficult to store, analyze, and interpret. This problem has given way to a new era of "Big Data", in which scientists across various fields are exploring new ways to understand the large amounts of unstructured and unlinked data generated by modern technologies, and leveraging it to discover new knowledge. Yet, despite these advances, healthcare, the largest global sector in market capitalization, healthcare information is viewed a-posteriori and often even post factum. Consequently, decision-making remains unscientific, haphazard, unsatisfactory and highly variable in quality. The domain of health care is data rich, with enormous advance taking place each day in all areas of clinical diagnosis, management, delivery and outcomes. Effective use of Big Data in healthcare is the analysis of quantifiable person patient data of multi-domain complexity: medical records, risk scores, sensor data. This has been enabled by the development and deployment of machine learning approaches. ML and AI only now make it possible to unravel the patterns, associations, correlations, and causations in complex, unstructured, non-normalized, and unscaled datasets. These datasets and their attributes include, voluminous, high-dimensional, time-variant, spatial-variant, and non-cumulative data. The processes used, improved and devised by the large technology companies and SMEs, for diagnosis, treatment and health detection are what is meant by "personalized medicine". Would it be possible for healthcare to coalesce product-based, service-oriented and system-enabling aspects as economic healthcare? Confluence and improved currency of data-rich technical environments => discovery of non/comprehended knowledge => translation of knowledge into actionable health care. Application of ML tools is also supplemented by the widespread adoption of Electronic Health Records. EHRs allow patient data to become more accessible to both patients and a variety of physicians, but also researchers by allowing for remote electronic access and easy data manipulation.

12.2. Tools for Patient Education

Prior to the formal disclosure of health conditions, an individual may perceive a variety of early symptoms that may cause them to suspect an illness. The onset of distressing symptoms is frequently accompanied by a similar level of anxiety. Completely normal and benign health concerns may prompt a visit to the doctor after consulting relevant symptoms online, exacerbating the burden on healthcare services and misusing the already strained resources. Providing clear, understandable information related to a condition, such as test findings or management options, dramatically reduces anxiety and is driven by comparable growth in information retrieval, with online searches becoming individuals' first port of call. However, any misunderstanding or misinterpretation of care content could have an undesirable effect on patient experience and health-related outcomes.

As a consideration for oncology care, developed a provincial-wide evidence-based decision aid to allow prostate cancer screening with a patient-centered approach. As individual preference plays a considerable role in determining screening uptake, personalizing care content, such as a decision aid, may have an impact. The integration of well-established psychological principles such as tailoring, framing, and heuristics into web-based content has been used to improve health-related choices, yet, until now, the application has been restricted to narrow or one-off health concerns.

The advent of artificial intelligence (AI) technology is widely expected to substantially transform and benefit diabetes education and counseling. Within the vast clinical databases of hospitals and professional organizations, a wealth of patients, medical, and drug databases have been accumulated. The provision of massive data sets provides a basis and platform for the establishment of an education diagnosis and strategy selection system for patients with diabetes. There have been increasingly in-depth studies of the use of AI technology in diabetes education and counseling, and its applications in text communication, education and counseling, knowledge recommendation and retrieval, image and video teaching, intelligent question and answer, etc. With the rapid rise and widespread application of AI technologies, the healthcare system in the future is expected to work more efficiently than ever before.

13. Integration Challenges

The successful implementation and use of AI-based solutions in a clinical setting requires overcoming various challenges. Firstly, collaborating with clinicians: implementing and using any AI technique in medicine must combine the expertise of physicians and data scientists, who must work closely and continuously together to produce efficient, robust, and reliable models that the clinicians will accept and use in practice. The physician must understand how the model proposed by the data scientist is automated, considering its assumptions and rationale, because when human lives are at stake everything must be in the decision-making process. On the other hand, the data scientist must learn what is clinically significant and how to clean and preprocess health records in a way compatible with the domain of his analysis and avoid the temptation to take everything in the medical record for granted.

A second challenge is formulating a model: once a prospective collaboration has been established, the first question concerns the problem to be solved using a predictive model. All predictive models require an assumption regarding the risk reduction that the clinical setting tolerates if a pre-defined set of features is known. This, which is the most clinical of the questions, and hence the most paradigmatic of the complex interaction that such a model would trigger, must be carefully analyzed and understood before any question is posed concerning features selection or the kind of machine learning approaches to be used.

Another challenge is the evaluation of the proposed solution: once the model has been formulated, a performance assessment must be provided before the data necessary to evaluate the proposal can be analyzed. In an AI community overwhelmed with metrics, the only advice is to be clear and transparent regarding advantages, disadvantages, and meaning. It is also essential to be clear and transparent regarding the consideration of prediction uncertainty. The AI branch of knowledge dealing with uneven classification errors and costs is named 'cost-sensitive learning'.

13.1. Technical Challenges

In healthcare, novel technologies are rapidly being developed to process big data and for efficient clinical decision support. Yet, production environments are vastly underdeveloped or entirely lacking. There is little if no tooling, design patterns or best practices available to efficiently acquire, harmonize, store, process, develop, test, deploy, validate and re-evaluate data-driven modelling in clinical datasets. Hence, there is a crucial need for a production-level platform tailored to the healthcare domain for the streamlined analysis of big data in machine learning (ML) applications at scale. There are many hurdles to overcome when transitioning from data science research prototypes to production-grade applications. This is particularly pronounced in the healthcare sector where vast amounts of heterogeneous types of complex clinical data need to be integrated into structured, machine-learning-ready formats for analysis downstream. Heterogeneous data flows comprise both structured and unstructured data sources. Structured datasets can be highly heterogeneous with multiple types stored in different EHR or clinical database systems, while unstructured data contains free text information either as clinical notes in "locked boxes" with inaccessible databases or as image files. The development of a data analysis pipeline to be integrated into the output for downstream use requires harmonizing these heterogeneous data types into structured formats. Moreover, such pipelines would need to account for high volumes of data potentially arriving in real-time.

The healthcare industry is highly regulated and comprises complex requirements with respect to confidentiality, data safety, ethics and clinical validation and implementation. These characteristics of complex datasets and strict healthcare infrastructure present a novel challenge for AI-native developers and data scientists seeking to deploy data-driven solutions in the healthcare sector. Models must outperform existing best-of-fit heuristics and must be validated for clinical reproducibility before they can be considered for real-world deployment. The healthcare industry therefore generally does not favour a rapid iterative or agile approach to data or model development. In addition to the challenges above, there is also a requirement that all sensitive data contain meaningful patient classifications. The organisation of EMR data is heavily siloed. The vast majority of health data in the form of clinical notes are stored in unstructured formats and remain unexplored while electronic health record systems are often unable to analyse or compare data across institutions.

Generating actionable clinical insights from prior advance sick incident (ASIs) using similar data from cut-off collaborative care has not been addressed and is an ongoing need at many acute hospitals. While corroborating knowledge discovery has been established for other data types, the peruse of knowledge from unstructured clinical narratives remains challenging.

13.2. Cultural Resistance in Healthcare

Innovation, including digital innovation, is culturally resisted by healthcare professionals. This leads to a cautious approach with sub-optimal uptake and scaling, resulting in diminished benefits for health system sustainability and affirming some skeptics' concerns. Cultural perspectives on innovation, including systems of meaning, values, rules, and beliefs held by a community about innovation, technology, and change in organizations and interiorized over time, are suggested to be a fruitful avenue to better understand how this resistance is manifested and importantly how it can be better addressed.

Front-line healthcare professionals collectively and individually build cultural frameworks regarding new digital technologies that go beyond abstract arguments. They weigh up new technologies in light of their historical, social, and occupational experiences, collective interpretations of the operating environment, and everyday routines. These cultural frameworks heighten suspicions about many current digital technologies, interpreted as over-engineered elaborate systems that are less likely to succeed than previous technologies with simpler affordances.

Managers and executives from all healthcare organizations reportedly perceive rising skepticism in front-line workers towards using technology. However, many senior executives believe that clinicians on the front line are not properly consulted and are not included in discussions about innovation development and implementation until they are needed for the last mile. Very few front-line healthcare professionals in the visits have been engaged to co-design or co-create digital technologies with suppliers. From the interviews, it is believed that front-line healthcare professionals are not consulted at early stages of selecting, designing, and developing digital technology, or are excessively consulted with ineffective design input sought. By the time the system is deployed, it is often too complex to integrate with routine practice and viewed as additional work with limited benefits.

Front-line workers questioning the justification for and value of digital technology, including embarrassment, tension, and distrust toward organizational actors directly involved with the technology, are viewed as cynicism, distrust, and fear toward those. The decision to implement a new information system is framed as a top-down edict imposed from above rather than as the result of an organization-driven, deliberative, and participative process. Clear, timely, and objective information regarding the considerations on how the specific decision is better than alternatives is often lacking by organizations, as is channeling feedback from the ground regarding this decision. Technology confidence often plummets when accessing new technology. Trust in people/support in control/on the technology itself is negatively affected. New technology is likened to a new organizational earth. The resulting skepticism resembles scepticism from the medical data ecosystem debate, and from early accounts about a necessary cultural shift for the success of digital innovation in healthcare.

14. Conclusion

The advent of big data and AI (Artificial Intelligence) presents a tremendous opportunity for improving population health and clinical care as a whole, and for personalized medicine in particular. Data collection and storage technologies have proliferated fundamentally changing the way in which decisions are made in a variety of fields, from business to cybersecurity and sport to urban planning. However, the evolution of healthcare and biomedical research, especially in terms of the use of big data and AI, has been relatively slow. This is likely due to the need to integrate from heterogeneous and disconnected data usually utilising disparate data types. Moreover, patient care and biomedical research usually relies on multi-level data with different resolutions, from a single cell to a whole population. On top of that, protecting the data privacy and security of patients and research subjects is of utmost importance.

Healthcare organizations rarely have sufficient data to train AI models that would be generalizable, especially for hospital-scalable free pre-processing methods for interpreting ubiquitous but machine-unfriendly images. Thus, even if some healthcare organizations do have relatively clean and large data, they are unable to use pharmaceutical data directly due to vendor lock-in of commercial EHR systems. Moreover, sophisticated AI approaches imply massive processes that usually require expensive multi-GPUs across high-performance computers. Thus, there is a need for a scalable AI-bid data approach that i) co-extracts high-level features and metadata along with broad-data integration and data modelling across cloud-edge systems, ii) embraces and leverages business ecosystems along with data pre-processing and intelligent algorithms and knowledge transference, iv) assures uniformly accurate and robust AI models be self-improved within local healthcare organizations.

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