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Harnessing Artificial Intelligence and Big Data for Transformative Healthcare Delivery

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Abstract

Artificial Intelligence (AI), Big Data Analytics, Cloud-Computing & IoMT can help create a full change in the way health-care delivery is executed and assimilated in smart cities in healthcare. The convergence of Artificial Intelligence (AI) and the IoT (IoT) has given birth to a widely spread digital phenomenon known as the Internet of Medical Things (IoMT). IoMT only overcomes external resource limitations by extending device capabilities for better knowledge design based on efficiently fused context specifications. In-built AI technologies in digital health gadgets, as an instance of IoMT, can improve the quality of the health-care delivery system. Second, it also manages the enormous quantity of digital health data and addresses the incapacity of entities to examine the data and mine circumstances to draw evidence-based conclusions. The Internet of Medical Things (IoT) promotes and mandates the frictionless interactivity of more connected products and services. As an example, health-care delivery in smart cities focuses on improving the quality of life (QoL) of all the citizens of connected smart cities. A data-informed health-care delivery system, where health-care resources are fabricated based on the historical population pattern and demographic approach, can help to efficiently utilise scarce health-care resources and eliminate places and times devoid of a health-care resource.

Both Big Data and Health Informatics have become the buzzwords of Digital Health and the Health 4.0 trend during medical actions and clinical studies. The historical development of this field is first reviewed. The attractiveness for health stakeholders to efficiently manage the growing demand of patients' data to be utilized for health alerts and disease predictions is pointed out. The issues such as data security and integration from heterogeneous data sources are reviewed as well as a two-tiered structure to combine shallow and deep learning as a solution framework is detailed with test cases in explorations of patients' clinical records and remote health devices (IoMT). Overall, the hybrid techniques have a bright prospect to proceed with the AI innovation in the health area with many more applications and tests in practical scenarios.

Keywords: Artificial Intelligence (AI),Big Data Analytics,Healthcare Innovation,Predictive Analytics,Precision Medicine,Machine Learning,Clinical Decision Support,Health Informatics,Patient-Centered Care,Data-Driven Healthcare,Electronic Health Records (EHR),Population Health Management,AI in Diagnostics,Medical Data Integration,Real-Time Health Monitoring.

1. Introduction

The adoption of Artificial Intelligence (AI) and Big Data (BD), coupled with Cloud computing and the Internet of Things (IoT) technology, has impacted healthcare. There has been a surge in digital health applications where contemporary information and communication technologies are used to manage illnesses and health risks and to promote wellness. This includes wearable devices, mobile health, telehealth, and telemedicine. Such applications respond to the increased demand for better patient management with more efficacious healthcare delivery. This evolution has the promise to improve access to healthcare, reduce inefficiencies and costs and provide a more personalized and, perhaps, a more humane healthcare. However, before AI applications can be used in healthcare, they must be "trained" using clinical or synthetic data.

A distinct and valuable asset of the healthcare sector is clinical data. There is a large variety in clinical data, such as demographics, medical notes, physical examinations, clinical laboratory results, etc. The emergence and wide availability of advanced analytics, machine learning (ML), and AI techniques offer numerous possibilities for transforming clinical data into meaningful and actionable results. Healthcare stakeholders

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such as hospitals, lab and imaging centers, research centers, and biotechnology and pharmaceutical companies can use analytical techniques to harness the data's power for predicting future outcomes (e.g., disease risk) and determining the best action for the current situation (e.g., diagnosis or treatment).

Despite the wide availability of clinical data, there is still a great need for more precise and focused data to build effective AI models. One approach to generating such high-quality data is by generating synthetic data. Synthetic data refers to any production data applicable to a given situation that is generated to meet specific needs or conditions. The resulting synthetic data can be qualitatively and quantitatively very similar to the original data while being privacy-secured. The generation of realistic, synthetic, behavior-based sensor data is a critical step in testing ML techniques for healthcare applications. Synthetic data generation methods can be classified into two categories: simulation-based and model-based. 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. Given a series of observation data from the original appliance, and the parameters of the trained model, synthetic sequences of varying lengths can be generated.

1.1.Background And Significance

For centuries, most medical knowledge remained in clinics, textbooks, and doctors' brains. Now it is being digitized, structured, and centrally stored at an unprecedented rate. Data will increasingly come from nontraditional sources, such as social media, telemonitoring devices, and even direct genomic sequencing. Structured and unstructured data can be harvested, stored, and analyzed using distributed solution architectures. Knowledge storage and diffusion will shift from the analogue world to the digital. Knowledge will be continuously obtained from the data rather than interpersonally transferred. These rapid and transformative changes were fueled by scientific daring, free-market economies, and global architecture evolution.

Beniger contended that earlier information revolutions, such as the introduction of clocks, printing presses, and telecommunication, were driven by an explosion of data caused by new technologies. Empirically, these information revolutions transformed society, communication, and the economy. They were closed social systems, which means that the revolutions only modified the status quo and scope of the variables involved in the respective systems. This time, there is the added dimension of the emergence and promulgation of open systems. Open systems consume local resources but dissipate global resources, if unchecked. Earth is captive of a global climate and resource crisis exacerbated by new technologies. Nevertheless, humanity evolved in closed social systems, and it did not foresee the advent and rise of open systems.

Equ : 1 Predictive Health Risk Scoring (Logistic Regression Model)

$$P(\text{Disease} = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}}$$

- **Purpose:** Predict likelihood of disease based on patient features $x_1, x_2, \ldots, x_n$
- **Use Case:** Early diagnosis, hospital readmission prediction

2. Understanding Artificial Intelligence in Healthcare

Artificial intelligence (AI) refers to those computer systems that are capable of mimicking or altering human abilities. It is the ability of a computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. AI systems are trained from data already collected, and are able to alter their behavior, based on experiences and learnings. Three sub-disciplines are commonly distinguished within artificial intelligence: 1) Machines that can manipulate symbols (primarily language, which is the focus of natural language processing); 2) Machines that can solve problems (with the knowledge of heuristics or algorithms); this is minimized in probabilistic versions; 3) Machines that can learn (this covers both supervised and unsupervised learning models). Achievements in one of these fields often are unrelated to developments in the other fields, so that a distinction is useful. AI in healthcare often implies some combination of these three categories.

While there is no universal agreement on what constitutes 'big data,' it does refer to data that is too large to be processed and analyzed by conventional approaches within a reasonable timeframe, limiting the insight that can be gained with these conventional approaches. The term encompasses various interpretations, such as data that is too large, too complex, too fast, or too diverse. On the one hand, big data refers to data that is so large that it is difficult to handle, process or analyse. On the other hand, big data technologies enable handling more data, allowing the storage, processing, and analysis of larger

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datasets than was feasible before. Measurements are often launched and gathered by devices that fall under the umbrella of the Internet of Things (IoT) or its medical version, the Internet of Medical Things.

2.1. Definition and Scope Healthcare organizations are challenged by important changes in cultural factors affecting the perception of health and the relationship with health and social care services, demographic factors related to the aging of the population, with attendant increase in co-morbidity and chronic conditions, financial sustainability, and organization of health services. Healthcare delivery processes across the globe are now starting to embrace a new paradigm-complete delivery processes of health services rather than just parts of them. The goal is to improve care pathways through a systemic approach taking into consideration the entire continuum of services addressing a patient in each part of the delivery process. Management and operational improvement through change-in-resources and reengineering will be required, often at system level across sectors and agency boundaries. This will have a considerable effect on workforce and technology in the healthcare ecosystem.

Emerging technologies in Big Data, Cloud Computing, Artificial Intelligence and Robotics are the key enablers of the new paradigm, but their introduction in the healthcare industry is fraught with pitfalls. These have basically a twofold nature: i) technological factors such as interoperability, security, maintainability, stability and regulation, and ii) organizational factors such as applicability of new techno-organization solutions, employee acceptance and opposition, work-based training and education. Healthcare delivery especially in hospitals is dominated by the human factor. Personnel acceptance of new technologies and working methods is crucial for the successful introduction and deployment in daily operation. Acceptance is often hampered by skill deficiencies, and communication inadequacies. Moreover, opportunities provided by technology are often misconceived or neglected, with attendant limited benefit realization and ROI.

The growing gap between fast advancing technology and its insertion in daily operation requires systematic and orchestrated innovation management in the healthcare ecosystem, addressing both technology and organization as interdependent systems rather than in separation. Thus far this paradigm shift has not been accomplished. In this paper a systems approach for a multi-level ecosystem-wide research framework on managing useful technology insertion is proposed. An exhaustive state of the art review of both systematic and orchestrated innovation management in healthcare is provided, highlighting current knowledge and presenting crucial challenges for research.

Equ : 2 AI-Driven Treatment Recommendation (Reinforcement Learning Value Function)

$$V(s) = \max_{a} \left[R(s,a) + \gamma \sum_{s'} P(s' \mid s,a) V(s') \right]$$

- **Purpose:** Optimal treatment policy in dynamic clinical settings
- **Use Case:** Personalized medicine, adaptive clinical decision-making

2.2. Types of AI Technologies Machine Learning, Neural Networks, and Deep Learning are subsets of AI that involve algorithms and statistical models enabling computers to perform specific duties without explicit instructions. The system is trained against examples (input data): supervised when the examples are labeled, unsupervised when they're not, and self-supervised when there's no explicit labeling. Similar techniques can also be applied to deep learning where computational models with multiple processing units acting in moderation enable analytical objects to form hierarchical representations. Various approaches based on the type of data use cases are also grouped into feature-based classical machine learning, convolutional neural networks, recurrent neural networks, multi-view multi-modal, and pre-trained language models.elaborated AI techniques used to transform data into models to automate clinical tasks and to which examples systems implementing AI techniques contribute. Key implementation barriers such as technical, financial, regulatory, and ethical challenges are reported.

Many have developed AI models analyzing healthcare-related data such as numeric tabular data in prescription data, medical history, or drug reaction. Challenge examples reported include: Drug response predictions; Evaluation of coherence between cancer-related drugs and genes; Predictions of responses to certain psychiatric treatments with clinical features. Other developed models address the related but broader challenge of predicting unwanted drug effects such as drug-drug or drug-gene interactions, adverse effects, or drug overdoses. Pilot use cases are a variety of classical machine learning, ensemble methods, and deep learning algorithms. One recent success in using natural language processing to analyze unstructured semi-structured data is broadly word-based embeddings with generative pre-trained transformers to analyze patient encounter notes. Expert statistical methods such as competing risk are used to account for confounding factors. Extensive pilot studies have been conducted in multimodal representations. A coverage gap in developing and validating AI models analyzing datasets containing time series continuous measurements (e.g., vital signs, lab results) is found.

2.3. Current Applications in Healthcare With the emergence of new technologies, Artificial Intelligence (AI) has experienced extensive advancements in all aspects of life, including healthcare. Unquestionably, it is one of the most prominent technologies that have gained the attention of both public and private sectors for its wide range of applications. A plethora of contemporary AI-enabled diagnostic systems have been architected and validated to analyze relatively simple data formats such as text, images, and videos in regional medical domains including linguistics, radiology, pathology, and cardiology. Nonetheless, to accelerate the development of AI, address issues and shortcomings, and identify areas of application in healthcare. Most of the mHealth systems for data collection and manipulation were designed in middle-income economies. Other researchers presented audio-visual technologies, such as retinal screening, diastolic murmur detection, malignancy classification detection from microscope images, and breast cancer detection using low-cost cameras that are directly integrated into smart mobile phones. Such sensing is used to facilitate direct, affordable interaction with patients, which is conducive to early diagnosis of cardiovascular diseases, tuberculosis, diabetic retinopathy, and breast cancer. A smart device that helps make informed parental/caregiver responses in emergency when encountering sick children is presented to reduce medication errors in pediatric emergency care. Another user-friendly, mHealth-enabled smartphone-augmented 2D-3D video-stereovision device for stereo vision and telehealth monitoring of ocular parameters is presented. An economical application of augmented reality for self-testing of tear parameters to monitor dry eyes, which is widely distributed in the population. Infectious disease epidemic prevention and control model to utilize AI technology in surface-emitting lasers, facilitate wireless healthcare system and wireless cellular network technology advancement to deploy health kiosks, prevent the spread of Covid19. Attention-based natural language processing for clinical text preprocessing is presented. Facilitation of ensuring timely patient visits to the acute care system and applicable work warrants for the public's interest is put forth.

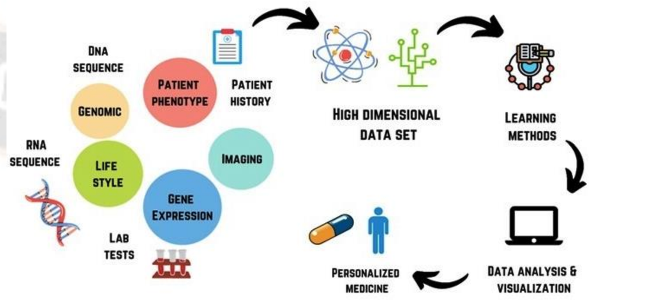

Fig : 1 Artificial Intelligence for Research in Medicine and Healthcare

3. The Role of Big Data in Healthcare

The history of digital healthcare began in the early 1960s with the inception of computer-based healthcare systems in hospitals for the electronic management of patient data using Radiation Therapy, Pathology, Pharmacy, Hospital Information System, and others. Encouragingly, the past few decades have seen rapid growth in the convergence of medicine and informatics as novel health technologies, such as microarrays, gene sequencing, imaging through Computed-Tomography (CT) and Magnetic Resonance Imaging (MRI) machines, Health Records Management Systems, and smart mobile devices, collected astronomical amounts of structured and unstructured healthcare data. However, it is observed that these digital infrastructure developments have not yet replayed the anticipated dividends in the form of personalized effective treatments for various illnesses except for a few cancers and some rare diseases. Medical data-driven insights into these cancers and diseases have effectively been utilized to assess their risk-based development, detection, and treatment response prediction. Besides the advances in understanding diseases development and drugs discovering platform properties, such as target identification, drug repositioning, and drug development, it is widely expected that Big Data-based insights, combined with Gold standard Biological experiments

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and literature, will dramatically accelerate the discovery of new drugs.

Although the potential opportunity of Big Data for personalized and effective treatment of other diseases is large, it is disconcerting to see little examples of this usage in healthcare, that is, treating Alzheimer's disease, Osteoarthritis, and Diabetes prevention/management. The major reason cited for this is the severe lack of patient data availability for conducting machine learning (ML) experiments in opposition to the genomic data availability, which was fortunately made open-source by the Human Genome Project initiatives. However, validated test-sets of patient data with follow-up and outcomes can be released by the hospitals or custom-designed technology-based applications similar to open-source databases of genomic toxicity and drug-drug interaction [6]. Upon obtaining data, an opportunity is presented to understand the trades-off between capacity, accuracy, and time-budget involved in building predictive models for patient safety. A successful case is an opportunity to extract features from Environmental Log-data to dramatically accelerate drug target identification. Such efforts can encourage patients to contribute their clinical data to external repositories to more effectively fight diseases.

Equ : 3 Big Data Integration Model

$$D_{\text{total}} = \sum_{i=1}^{k} D_i \cdot w_i$$

- **Purpose**: Aggregate multi-source healthcare data (EHRs, wearables, genomics, etc.)
- D_i: Dataset from source i; w_i: Weight based on reliability or relevance
- **Use Case**: Unified patient profiles, holistic analytics

3.1. Definition of Big Data

The term "Big Data" has gained significant attention since the early 2000s. Its significance arises from the data explosion scenario. Twelve Exabytes of data came into being from the dawn of humanity to 2002, whereas it is estimated that 44 Exabytes of data came into being in only 3 years—2007, 2008, and 2009. Google alone made 12 Petabytes of data available daily. Big data is defined by 5Vs: Volume, Variety, Velocity, Veracity, and Value. Volume refers to the vast amount of data, which can be high in Petabytes or Zettabytes. Variety refers to the unstructured nature of data. These are Text, Records, Audio, Video, Images, Places, and Metadata. For example, on Twitter, data comes from texts in the form of tweets, URLs, location data, and so on. Velocity refers to the speed at which this data is in motion, which can be real-time or batch. Veracity refers to the level of trustworthiness of the data source. Value refers to the usefulness of the data once it is retrieved and processed.

Healthcare big data has been defined as clinical and non-clinical entities that have the capability to store structured and unstructured data for the entire lifespan of an individual in its raw format. The healthcare system is one of the oldest fields in which data is generated. Patient data is recorded as disease, treatment, and recovery. Healthcare data analytics works on both clinical and non-clinical entities to make the best decisions and healthcare outcomes possible. On the clinical front, this data remains to serve as Electronic health records (EHRs) or Electronic medical records (EMRs). In countries with developed and semi-developed healthcare systems, some EHRs are maintained in public data formats. The analytics on these records can provide predictions about possible improvements in healthcare. Numerous text-mining and preprocessing techniques are now available to work on unstructured healthcare data. A combined analysis of these (EHRs, EMRs, and many more medical data stores) can alleviate the clinician's job and aid in building an improved prognostic framework.

3.2. Sources of Big Data in Healthcare

The healthcare industry is one of the most prominent fields for big data application. Many factors contribute to healthcare big data such as vast health records storing the health history of patients, hospital–visit records containing billing history and treatment received, disease and diagnosis databases containing symptoms, treatment, and cures for diseases, epidemiological records of diseases and their treated and untreated stats like region, culture, and country specific, demographic data related to a specific region, population forecasts in terms of the age, culture, race, etc., and medical process records of the types and combinations of antibiotics and drugs used on a patient with disease information, physical environment, and lifestyle used on patients and the result of their treatment across various areas. Medical imaging and medical sensing devices with the current trend of telehealth, remote monitoring, and wearables also generate significant amounts of unstructured data in terms of text, videos, medical sound waves, health statistics like heart rate, blood pressure, etc. The inventive impact of combining all this data with organized or unstructured data from other industries like the pharmaceutical one can disrupt the healthcare industry and even create business-centric data sources. The combination of unstructured and structured health records and the customized system allowing treatment for a newly diagnosed disease can turn the healthcare industry upside down. Individuals with the broadest knowledge of health and non-health data may be able to identify an undiscovered aspect of many-related data and facts of interest in the field of generative learning. Healthcare big data sources include doctor-to-patient communication or vice versa communication containing prescriptions, explanations of diseases, lifestyle changes, etc., care-to-care communication containing feedback/opinion of care received, patient search query behavior, and drug and side effect reviews, searching queries, and enormous health-related usage, behavior approach toward exercises like walking, gardening, dance, meditation, etc., and electronic medical surgical appliances like pacing machine, oximeters, etc.

3.3. Data Analytics Techniques

Several opportunities exist in the healthcare sector for the application of Artificial Intelligence (AI). Some pertinent AI use cases support clinicians in their diagnosis (risk prediction, decision limit checking, anomaly detection) or simple record-keeping (medical note to text verification), improving the quality of healthcare and operational efficiency. However, healthcare data is often to a large extent unstructured or semi-structured, mainly in the form of clinical notes, images, videos, and patient-related records. Techniques such as image classification, text mining or natural language processing, and video analytics can use AI to derive meaningful information from the convolution of large unstructured data. Big Data in the health sector could improve therapeutic accuracy, warn of drug interactions, push patients toward earlier preventive screening, and change patients' behaviors through alerts for upcoming therapy deadlines; some of these opportunities seem easy to seize, but it is necessary to be properly equipped. The most important step is to hire expert analytics professionals who can identify problems from data and propose insightful solutions following the recent hype regarding structured querying language (SQL). Productivity can increase dramatically in the healthcare sector if the outlier detection efficiency or logging search capability are increased in a patient-volume dependent fashion.

Ample opportunities exist to enhance healthcare delivery using AI. Clinically relevant AI applications fall into categories of forecasting impending medical conditions using collected or streaming data (alerts) and triage support to prioritize patients for diagnosis and treatment based on clinical notes or other data sources. Conventional AI classifiers utilize spectral and temporal features extracted from sensor measures for cardiology applications. The temporal features typically originate from simple statistical measures such as mean, standard deviation, and sum, across defined time frames. The derived features are neither patient-specific nor characteristic of the measured physiological parameters, which leads to inaccurate risk assessment and insufficient sensitivity to new patterns. Enhanced statistical texture analysis techniques can be combined with conventional features to transform the signals into a 2-D image format, being common in image processing. Risk prediction techniques could be employed at the individual patient level to alleviate the burden of remote patients or prevent emergency care overload. More labeled training data with templates reflecting possible healthcare machine learning applications, such as time-to-noise (x-axis), Beat-to-Beat variability (y-axis), and risk scores shown as statistical text (red versus blue), could be generated by simulation techniques.

4. Integrating AI and Big Data

Health systems worldwide are grappling with the pressing need to improve their performance in terms of quality, costs, and accessibility of healthcare services. Burdened by ever-needy patients with multiple chronic conditions and a lack of financial resources, a paradigm shift is urged. Currently, the lack of effective population health management is a major impediment to the quality of care and costs. New approaches are needed that ensure affordability and meet the individual's evolving needs. For health systems, this entails moving from a provider-centric to a more patient-centric perspective on care delivery. A potential route for transformative healthcare delivery improvement is the development, implementation, and subsequent integration of widely-discussed technologies such as Big Data, Artificial Intelligence (AI), the Internet of Things (IoT), and Blockchains.

The combination of big data, AI, IoT, and blockchains has the potential of transforming healthcare delivery through its capability of unprecedented insight generation. Big data refers to data sets characterized by a variety of volumetric or velocity patterns often demanding extra analytical capabilities. The models of data analysis on big data are being significantly extended by AI. AI concerns systems that perform tasks traditionally done by human beings that require cognition capabilities. The model of autonomous agents is useful to realize the different entities involved within current disruptive technologies, including services and systems. Subsequently, three important characteristics of autonomous agents can be further elaborated: proactivity, social ability and intricacy. The wide availability of data alone can't leverage insight generation: Data must be analyzed. Here, diverse AI- and data analytic-driven healthcare solutions are emerging, including predictive models, data mining, data visualization, and text mining. The viewpoint offered in this study is that the disruptive societal influence of these technologies ultimately depends on their successful integration into existing healthcare delivery networks. Current digital health solutions are isolated applications that rarely address the interdependencies within healthcare processes and that hardly attain their full scale of operations. There are many roadblocks to a successful and sustainable integration of smart technologies into the established healthcare delivery.

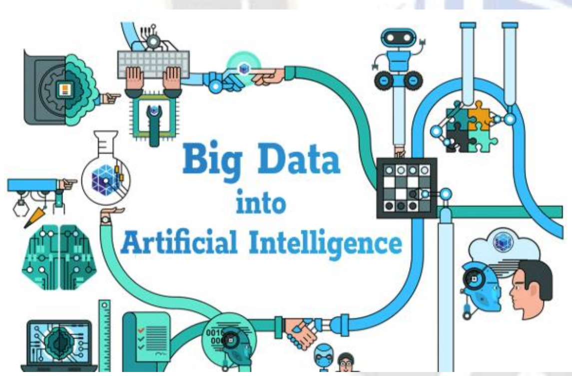

Fig : 2 Big Data into AI

4.1. Synergies Between AI and Big Data The digital health phenomenon represents a significant paradigm shift in healthcare innovation, enhancing the quality of services while personalizing them to meet individual patient needs. This transformation offers the potential to monitor health in real-time, irrespective of geographical location, improving costs, accessibility, efficacy, safety, and portability. Digital tools, devices, applications, services, and technologies collect, archive, integrate, analyze, and visualize a vast array of health data to evaluate health conditions. However, the management of healthcare big data raises a set of major issues and risks for fundamental players and operators, necessitating the preparation of responses to this transformation. These include risk assessment of data processing within the healthcare sector, reconceptualising the relationship with patients, exploring a cultural change in digital transformation, seeking a political commitment to pursue firm regulations, establishment of new protocols for more efficient and secure transmission of sensitive health data, and recognizing sustained investment in the detection and containment of emerging threats. The unprecedented volume, variety, and velocity of big data flows (BD) collected by a plethora of systems and devices to monitor health conditions and their risks necessitate fundamental changes in managing healthcare-related data. Governments and healthcare organizations are exploring AI and analytics techniques to manage the problem of healthcare data explosion, consolidate organizational resources, and develop data-driven and digital governance. The emergence of big data analytics (BDA) is promising to optimize current processes and systems while providing opportunities for new models of care to corporations and operators providing healthcare services. The investment deployed in the development and advancement of health analytics must be effectively leveraged to promote innovation and resiliency. Effective and efficient BD management has the potential to produce considerable benefits across a multitude of dimensions, which is crucial for corporate healthcare organizations looking to drive improvements in care quality, efficiency, and safety.

4.2. Case Studies of Integration Artificial Intelligence (AI) can be defined as the emulation of human thought processes in a computer environment for the purpose of decision-making, combining machine learning, natural language processing, and data mining. Healthcare AI development in pivotal methodologies requires datasets, research focus, and AI algorithm development, which in turn must meet necessary ethical requirements. As Covid-19 has demonstrated, the importance of using healthcare data to isolate trends, outliers, link different stratifications, and predict future developments has been amplified. Various methods for integrating AI with healthcare data have been tried and tested globally, with more focus placed on bigger datasets and integrated analyses as opposed to smaller. When it comes to developing AI-driven healthcare systems, the process often begins with data capture.

There are many different types of health data, divided into source, granularity, format, access, and structure. Incorporating structured and unstructured text data in a manifold of formats yields a proliferated volume of knowledge with various granularity levels for big health data. However, extracting useful phenomena when interfacing AI systems with real data in systemic biology applications is an open issue. One method that works well is to start with narrow domains of lower complexity and ease of adherence to rules, such as biomedical knowledge extraction from a single dataset of scientific texts or clinical narratives. Another approach is to use wellbeing interpretable techniques like unsupervised RNN grammars and variable selection methods to analyze high-dimensional candidate genomic data, then stemming hypotheses on disease-related variables with more target data types. Recently, work has also been conducted towards the management of personal data generated by health wearables, basic laboratory information, and administrative records. Data accessibility must be thoroughly considered at the beginning of the research project. The cost of processing zero-cost public data must be compared to the solution of developing strategic collaboration with data custodians for prototyping basic research.

5. Transformative Impacts on Healthcare Delivery

In recent years, how healthcare is delivered has changed dramatically, largely due to the advent of new technologies such as big data and artificial intelligence (AI). Such transformative technologies are being used by healthcare organizations for everything from sourcing new drugs to personalized treatment recommendations, improving patient engagement, and empowering patients to take charge of their own health. For newly emergent health tech enterprises, these technologies are being deployed to cut costs, reduce clinical errors and absenteeism, and minimize waste in all aspects of the healthcare value chain. As tools for early detection and treatment of diseases, they are being harnessed in outpatient care including medications, prevention of chronic diseases, nutrition, tech-based patients, and health outcomes tracking. For healthcare systems in developing countries, they hold the potential to reduce hospital stays, maximize the use of resources, and massively enhance access to care.

The digitization of the patient journey, where healthcare has been fragmented and delayed, will contribute to a more coherent way of handling patients' care. Intelligent platforms, used to manage the flow of patients and make sure the right people are assigned to the right tasks at the right time, will eradicate obstructed flows and will make care more lean. Using AI and big data will facilitate improving treatment, e.g., using a recommender system making patient-tailored dietary advice, analyses of posts on social media looking at public sentiments on healthcare professionals, or using machine learning for prediction of

Fig : 3 The Impact of Digital Transformation in Healthcare

5.1. Improving Patient Outcomes

Recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency and improve patient outcomes. In clinical care, AI technologies can aid physicians in diagnosis and treatment selection, risk prediction and stratification, and improving patient and clinician efficiency. Standardizing, annotating and processing these data, while also ensuring patient confidentiality, scalability, and proper compliance with the regulations of the highly regulated healthcare industry is a significant challenge and the initial focus of these efforts is presented here.

The rapid development of electronic health records (EHRs) and wearable remote monitoring devices provides institutions with access to rich data sources. Despite their breadth, these data sources are not sufficient. The barriers to translating data science research into patient care are inadequate data quality, scarce resources, and high patient confidentiality needs.

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. Most electronic health record (EHR) systems store patient data in heterogeneous formats, sometimes combined with legacy systems. In addition to the structured data for medications, laboratory data, and imaging, there are large amounts of unstructured data like physician notes, discharge summaries, and reports. The EHR data has a significant degree of missingness, misclassification, and errors. Furthermore, high-dimensional data like telemetry, EEG, genetic, and continuous physiological data provide valuable clinical insights but require large storage and processing capacity. Harmonizing these diverse data sources can be a very time-consuming and resource-heavy process. In contrast to the large technology companies, most healthcare entities lack interoperability of their data sources, high compute resources, and large data science teams. Moreover, healthcare is a highly regulated industry, and there are complex requirements for patient safety, confidentiality, and ethics.

These characteristics of the healthcare landscape present significant challenges for the rapid and efficient development and deployment of AI technologies. In contrast to many industries that readily adopted AI in products, the healthcare field has remained relatively untouched by the AI revolution. Excellent healthcare is highly complex and slow, making it difficult to assess and operationalize AI technologies. Furthermore, healthcare is a highly regulated industry, and there are complex requirements for patient safety, confidentiality, and ethics. These characteristics of the healthcare landscape present significant challenges for the rapid and efficient development and deployment of AI technologies.

5.2. Enhancing Operational Efficiency

Healthcare is very much data-driven nowadays, and the allied ecosystem for healthcare and life sciences is in for a transformative change as a result of the convergence of quantum computing, artificial intelligence (AI), and big-data technologies. Next-generation deep-domain AI models applied to big data could accelerate the pace of scientific and translational research across heterogenous imaging, genetics, and multi-omic high-dimensional big-data, leading to a new era of drug discovery, development, and personalized medicine. AI will play a key role in transforming traditional healthcare services to smart healthcare services with earlier triage and smarter detection, prognosis, and treatment of diseases. There are also huge socioeconomic benefits to be gained across health equity, ascending preventive health, quality of care, health outcomes, and efficiency of healthcare service delivery. The AI-based technologies originating from the academic research will also lead to the setting-up of service-based start-ups resulting in huge economic benefits through job creation and unifying the healthcare and tech industries across businesses and countries so that healthcare is not only socially beneficial but also financially viable and lucrative. The era of digital transformation in healthcare presents new opportunities to improve business processes and enhance operational efficiency. The health systems are large and complex multitasking operations. Executing these processes accurately and efficiently requires sustained interdependencies that foster organizational performance. Business processes rely on many types of heterogeneous data sources. Continual changes to existing data sources and increasing volumes of newly generated data create tremendous challenges in both characterizing new information and assessing its potential value. Therefore, the transformation of healthcare practices is inextricably linked to information analytics. However, transforming analytics practices in healthcare systems is often more difficult than anticipated. Hence, there is a fundamental lack of understanding on the shortcomings of proper pre-assessments of existing practices and system capacities. Adopting a systems theory view of organizational analysis through the lens of complexity science has considerable merit to guide enhanced information processing for the transformation of healthcare practices. This analytical framework captures succession rates in the lifetime of organizational routines and transformations of existing practices.

5.3. Personalized Medicine

The extensive application of digital technologies along with data generated through recent advances in molecular and cell biology and engineering sciences can transform medicine through individualized or personalized treatments. Personalized medicine is not just about providing patients with the ‘right drug’ in the ‘right shape’ at the ‘right time’ but also the ‘right dose’ derived from including/combining relevant resources that affect drug activity. Due to the heterogeneous nature of disease mechanisms presented in an individual’s system, personalized treatments have become elusive. To address this remaining challenge, an extensive and multi-faceted screening of multiple resources affecting drug activity is needed (focusing on a middle path). Although possible, it

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will be exceedingly difficult for humans to monitor and analyze data generated from thousands of cellular metabolism per second, hundreds of associated pharmacogenes, and environmental co-factors, which need to be transferred to astronomy scales . AI is at the heart of bias-free solution derivation to monitor, process, and integrate these big data. On the inputs side, datasets can be streaming from various sources that need simple pre-processing that can also be chromoseq run length normalized and visualized via autoencoders or T-distributed stochastic neighbor embedding platform. On the output side, recommendations of drug delivery systems, administration route, composition of drugs, and APD can be derived based on association with optimization criteria through various multi-objective optimization algorithms.

It is not a question of application but the extent of deployment of digital technologies and AI, which can fall on the red-to-green line of different approaches indicated by terms of fully manual, semi-automatic, and fully automatic assistance. In parallel with prescription clarity by elementary drug delivery systems, 1D system category screening through precision prescribing based on multi-source big data and AI can aid high-throughput collation of information on pharmacotherapy. The collective recommendation on the modes of delivery can also promote automatic exploration of formulation states and experimental design in the drug development pipeline. Less controversial are the clarity in the composition and ratio of drug formulation development through computer-aided pharma that can be linked with mode selection. The application range can expand via high-fidelity electric-like modeling for virtual patients to aid White-coat-free decision-making.

6. Challenges and Barriers

As health data becomes more ubiquitous, the advanced health analytics models powered by large-scale data create immense possibilities towards enhancing healthcare delivery, clinical and business decision-making, and improving health outcomes via actionable insights. This requires harnessing AI technologies to access large-scale diagnostics, clinical, genetic, genomic, health outcomes, lifestyle, socio-economic data, and health data analytics to predict and manage complex multi-faceted health issues. Although AI-enabled personalized care, timely diagnosis, AI-powered physical and virtual assistants, improved genomics interpretation, readmission prevention, health outcomes prediction, integrated EMR/ EHR/RI data ecosystem, radiomics, genomics, and pathology AI diagnosis have made significant progress, the journey of enhancing AI-enabled health data is still ongoing. This is due to various technical, usability, environmental, and ethical challenges.

First, the health data ecosystem is complex, fragmented, and disconnected with multiple types of datasets about patients' historical medical records, genomic, lifestyle, symptom, socio-economic, and environmental data. The need to connect diverse siloed, heterogeneous, unstructured and semi-structured data slows down new model training for diagnosis and daily workflows for data retrieval, interpretation, and presentation. The disconnected ecosystem also hinders data reconciliation on the same data subject across requests, causing difficulties in searching for relevant data for decision-making and increasing patients' risk due to poor decision data. Furthermore, most of the existing prediction models address a specific disorder instead of multiple diagnoses or diseases co-occurring in a patient. Hybrid and knowledge-embedding models are needed to combine primary features identified from existing ML- or knowledge-based models for attention towards crucial attributes, domain knowledge, and data reasonability into a deep learning model.

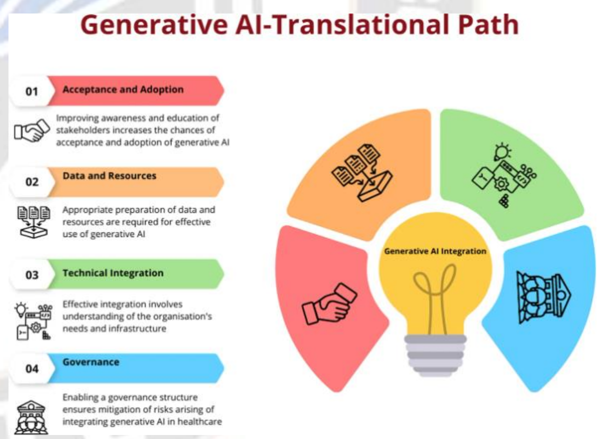

Fig : 4 Challenges and Barriers

6.1. Data Privacy and Security

Transformative big data analytics with AI will require extensive access to patient health information, which introduces new privacy risks. There is no regulatory model addressing how AI systems access health data and whether there are ways to protect health data in this era of big data analytics. The regulatory model in place for health data is based on a classic information model—one in which information collection and ownership are relatively haphazard and discretionary. Health data flow freely between organizations. New data-driven technologies can function without technical access to patient health information. The use of cloud systems and external databases with strong protections with appropriate regulatory oversight can improve many aspects of AI health applications. The core problem is that AI technologies for predictive analysis learn from the entire dataset available rather than the data on an individual patient basis. New regulations on data accessibility must accompany new data protection mechanisms.

Transparency and oversight of data collection and commercialization are vital. Academic medical centers, research institutions, payers, and regulators must have visibility into the access, use, and commercialization of patient health information. This oversight can take many forms ranging from careful provisions in contracts and shared regulations to periodic audits. A more formal means of privacy control that is missing is the ability to audit compliance and bilaterally enforce appropriate sanctions. Given that many medical institutions hold vast troves of patient data, this glaring absence of adequate privacy control should be urgently addressed. Moreover, scrutiny is required for studies showing real-world AI application performance. Developers must be made to adhere to clear standards regarding the extent and types of data used to validate study results. This would broadly have important implications across technology design and evaluation domains beyond health. Provisions should be made for appropriately weighing risks against benefits at the level of institutional or national regulatory bodies. There are also gaps in enforcement abilities for health technology design that would have broader implications.

Another necessary action relates to preemptive public involvement. The approach must be multi-tiered to maximize learning. Public data ought to be made available in advance for analysis and public cooperation. Broader datasets should then be employed for public inclusion at later stages. Creative methods of seeking public input should be employed to encourage public participation as well. AI health applications and their market forces are advancing rapidly. Regulatory authorities are moving cautiously. To protect privacy from the new and complex threats from AI, the public needs to be involved early and often. Otherwise, the health system will retain great promise but provoke trust issues and litigation risks.

6.2. Regulatory Challenges Today, artificial intelligence (AI)-based tools have shown to improve clinical workflows, enhance patient safety, aid in diagnosis, and facilitate personalized treatment. Cutting-edge AI technologies are reshaping healthcare, promoting significant achievements in various medical fields, particularly in imaging processing. In humans, results on classification, detection, localization, segmentation, and restoration of medical images have been produced. While AI-driven innovations hold the potential to significantly improve healthcare outcomes, ethical and regulatory challenges need to be explored and addressed because of their wide implications. This is even more necessary as some state-of-the-art tools come to light, some more area-specific, others more comprehensive in scope, many of which lack regulatory approvals and thus raise practical, ethical, and legal issues . Hence, the future challenge is to understand the major ethical and regulatory challenges related to AI technologies in healthcare so as to ensure their responsible development and adaptation to clinical practice.

Though substantial amounts of effort have been invested in explorative studies on the ethical issues concerning AI technologies in healthcare, several challenges remain. Thus far, the integration of AI in healthcare is fraught with a myriad of far-reaching challenges related to ethics, legality, and big data. First, the very notion of ‘intelligibility’ of an AI-based decision-making process is up for discussion given that some of today’s AI penultimate tools are opaque and inherently unknowable black boxes. Second, AI is trained on past healthcare decisions that may encode systemic or partisan biases. Third, the deliverance of patient care by software contractors is a departure from long-standing healthcare laws. This lapse raises the stakes for sovereign accountability of poorly executed AI, data privacy, data use, endorsement of medical decision-making, and non-democratic compliance, or patient empowerment. In addition, the ability of AI to reason about patients’ health should be constrained, as it is not evident that AI may be able to trace any ‘health law’, as it does survey healthcare data to surprisingly compute statistics on the relevance of patient features to diagnoses. Finally, the scientific and commercial desiderata driving a very appealing AI technology are sometimes at odds with ensuring more efficient workflow, better patient safety, better trust in the machine, better patient health, and so forth, with propensity for erosion of patient safety stip using training or validation samples, or lack of “justification info”.

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6.3. Technological Limitations Artificial intelligence (AI) has captured the collective imagination of medicine's practitioners and stakeholders. AI is understood to mean computational techniques, including machine learning, that depend on vast reservoirs of data. Its allure stems from the ambition of harnessing vast repositories of medical information to create resources and practices within health systems that enable stakeholders to learn more efficiently. AI systems are envisioned to improve care delivery. They might synthesize the state of scientific knowledge, develop rapid, focused online learning modules for care delivery stakeholders, and inform the creation of protocols for diagnosis, treatment selection, and assessment of effectiveness. Widespread enthusiasm for AI also takes a haunting form. It expresses a fear of missed opportunities for ameliorating cognition in health systems in the wake of the COVID-19 pandemic.

Although AI in its various forms has tremendous potential to enhance human capabilities, its long-term prospects in medicine hinge on how it grapples with a paradox at the heart of the healing art. The central and defining moral duty of healthcare providers is to use medical knowledge, clinical skill, and available interventions to safeguard and advance the health and well-being of patients. Achieving this duty requires making good decisions in the design and delivery of healthcare. Yet a characteristic of healthcare, and thus an obstacle to fulfilling the duty of care, is that medical knowledge is incomplete and the learning environment is noisy. The coronavirus disease (COVID-19) pandemic illustrates the challenges that arise from a novel pathogen for which safe and effective interventions are unknown. Prior to COVID-19, the health system had only a crude understanding of the ecology and pathophysiology of severe acute respiratory syndrome coronavirus 2. Evolving understanding came with evolving good practice, uncertainty, and the possibility of palliative care yielding unforeseen consequences.

7. Future Directions

Big data and machine learning offer the potential for a transformative leap in healthcare delivery if harnessed effectively in a health system that is already burdened by chronic disease and rising costs. The lessons learnt by industries that have adopted these technologies must be closely examined to avoid damaging the public trust in healthcare. Early projects that utilize AI tools need careful planning to protect the best interests of patients, healthcare workers, and the public at large. Therefore, a mixed methods approach that examines the best practices in healthcare models confronted with a similar change in paradigm is warranted. This is first a review of the current state of AI and big data deployments throughout the healthcare system, followed by a summary of the best practices found in healthcare models emerging from similar circumstances. Based on this examination, key points for future deployment of AI tools in healthcare are provided. These proposals will better inform stakeholders in the development and implementation of models and tools to duly enhance the quality of healthcare delivery. Healthcare systems, similar to many other industries, are seeing a dramatic rise in the volume of data that challenges the ability of humans to process. Patient data is a vital clue of patient condition and of the pathway to effective treatment. An explosion in the volume of patient data has the potential to allow healthcare systems to deliver a step change in health delivery. Computational advances in AI and machine learning represent an unprecedented opportunity to deploy tools to mine this data and fundamentally change health delivery.

7.1. Emerging Trends in AI and Big Data Healthcare is experiencing a significant digital transformation driven by the diffusion of Big Data and Artificial Intelligence (AI) technologies. Big Data in terms of the frequency, volume, and variety of data collected, has changed the traditional way of treating patients. These data include Electronic Medical Records and Sensors, and registered Continuous Data streams via thousands of sources. The digital health phenomenon promises to improve the quality of health services, shaping them according to patient needs, with the possibility to feed them preventively with a permanent information flow. The socio-political relevance of the phenomenon entails an understanding of how this is obtained in the selected countries. AI technologies are moving from computers to cloud computing and from cloud to the Internet of Things. In the healthcare sector, AI helps to manage costs, integrate data flows, automate and engineer medical processes. The novelty of AI in healthcare lies in the rise of open platforms and marketplaces providing cloud-based AI data services, and the integration of AI with Instant Messaging program bots and video-platforms, that broaden automated healthcare service availability, whilst offering tools for data storage and data organization with information retrieval tools, for patients and physicians alike. Service Robots are new usages of AI also in healthcare, where they provide both logistic support and operational assistance. Additionally, AI Applied scientific models, which process personal medical information, searching for answers within a knowledge graph of medical knowledge and AI procedural models, which emulate physicians' reasoning, searching for diagnosis respectively treatment paths. Open AI-based tools for healthcare are becoming free and widely accessible, threatening the historical model of relationships between clinicians and patients. The first selected trend is on AI cloud vision systems able to monitor videos streamed by standard surveillance cameras, providing on-demand notifications and ensuring an automatic documentation of every event. The second selected trend is the emergence of various Data-Cloud services that help consolidate payment and administrative information streams guaranteeing security and data-scaling facility upon contracting mutually agreed fees.

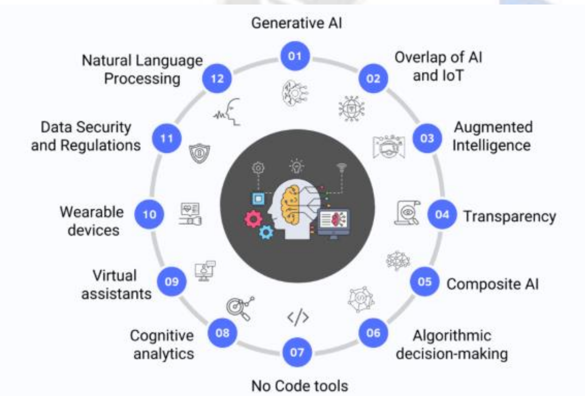

Fig : 5 Emerging AI and Big Data trends

7.2. Potential Innovations in Healthcare The healthcare sector is expected to grow significantly in the next few decades. Technology-related problems in healthcare delivery such as adoption, interoperability, integration with health ecosystems, and protection of enabled data have created a market for services and products. The aim is to identify unmet needs in healthcare delivery and develop AI-based solutions and services that can address them. The use of AI and advanced analytics in healthcare raises questions of sustainability. Early adopters of AI-based solutions primarily implemented them to gain a competitive advantage. Many of these early initiatives are still running with limited upkeep and scaling. Current and future development companies are transitioning from mid to large sizes, where compliance to regulations related to patient safety and medical treatments is imperative. All of this requires systematic planning and documentation of service provision processes. However, big data and analytics-related requirements are often overlooked. When the AI system is running, the reasons for its outcome are often poorly documented outside of the mathematical models themselves. This lack of understanding makes it hard to validate the solution and continue its follow-up development, which reduces the chances of its scalability and wider usefulness.

There is a fine line between ethical and unethical use of patient data. To market services both in-house and externally, there are more demands than just the formal assurance of data anonymization. The interoperability of all data sources and the architecture of the data lakes should be considered throughout the whole service lifecycle. Healthcare organizations are eager to consume data and analytics services. However, before these demands can be addressed, the whole supply chain must be developed. Service producing companies are often too small to be able to afford well-established quality and safety procedures. However, without proper documentation and controls, it is almost impossible to generate trust in the products, regardless of their obvious technology-enabled value.

7.3. Long-term Implications for Healthcare Systems Investigating applications and harnessing artificial intelligence (AI) and big data (BD) in healthcare could lead to the transformation of health systems into the healthcare services of the future. Such systems would encompass a combination of hospital-based services, community-based services, and home-based services. All services would deploy the principles of prevention, early diagnosis, and empowerment to maximize the adoption of health-promoting behaviors by populations. Analytics technologies and IoT hardware would create a comprehensive ecosystem of data sources, allowing for the synthesis of a 360-degree view of a person's health, lifestyle, and environmental context. Researching personal risk factors and their interactions would help calculate HDM, detection of changes to HDM leading to actions. In treatment-prescribing health systems, risk groups would be identified from the HDM of persons. A synthetic population model would be constructed from population mobility data.

Policies needing to be driven by a vision and incentive structure are outlined next. This is essential to ensure the ontology is able to evolve as decisions in health management change, and to align with measurements of health burden. A comprehensive and continuously updated record of the costs of the whole health continuum is needed. This would include damages done by the lack of action, costs of actions taken, and the benefits received from them. Health Coverage and Risk Pooling models would spread accessibility to the approach. A strong health management capability and credibility need to be built and maintained by high-level players with the cash flow, political, and management capacities to allocate funds optimally. Low-level players, consisting of healthcare associated industries and services, would need to be incentivized. Sustainable decision-supporting AI and BD analytics capability at the healthcare service level are core preconditions to operating on cash flows that grow exponentially.

8. Ethical Considerations

AI and Big Data are transforming societies in profound ways. They are also poised to revolutionize healthcare delivery, amplifying the effectiveness, accessibility, and affordability of medical services. While promising, the "AI in healthcare" sector also raises ethical and legal concerns as these algorithms obtain and process an increasing share of sensitive data concerning people's health, which may intensively affect their lives. Moreover, these issues are highly complex and multi-faceted, and need the involvement of various disciplines. Consequently, there is an urgent demand for research that elaborates on the ethical and legal ramifications of AI in the healthcare domain.

Healthcare AI tools can be used responsibly by informed stakeholders. With AI, a fine balance can be struck between the benefits of automation and the risks of over automation. Guaranteeing a degree of accountability and control over AI tools used in medicine requires the input of various watchdogs with a justified stake in observance of ethical norms. Processes for the responsible design and assessment of AI have been developed and remain to be improved, and can be operationalized and monitored in a watchdog environment to mitigate ethical concerns surrounding deployment of AI in healthcare.

Many of the issues raised feed into formal rules governing professions in healthcare, biomedical ethics and data protection, as well as into the design of AI. However, all researchers profit from analyzing this topic from the same angle simultaneously. A need for in-depth cross-sectoral collaboration concerning the ethical ramifications of AI in healthcare is evident, yet absent in the literature to date. At the same time, the rise of AI as an urgent issue for a broad audience of stakeholders constitutes an opportunity in this regard. There is a window of opportunity to spur productive interdisciplinary collaboration on the ethical ramifications of AI in healthcare. This collaboration does not only need in-depth analysis, but also action-oriented research on how human oversight through governance, norms, and design can be effectively ensured.

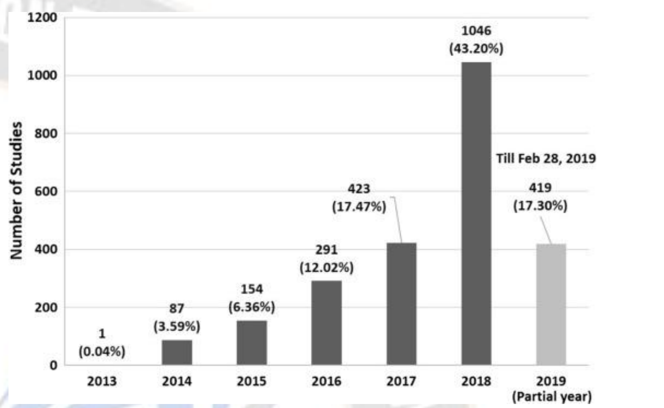

Fig : 6 Transforming healthcare with big data analytics

8.1. Bias and Fairness in AI

Artificial Intelligence (AI) models have shown remarkable performance in a variety of applications, ranging from vision to translation and even language understanding. In healthcare, various tasks such as triaging, diagnosis, automated clinical notes generation or medication recommendation have sparked the interest of the AI community. As the research effort rises, the claims that these models adopt with no (or not enough) human effort still remain the same. Emerging evidence shows that many of the data-driven clinical decision support tools that guide and improve healthcare delivery may be biased and therefore, not equally benefit each population. Particularly minorities and historically disadvantaged groups are at the risk of suffering from unfair model predictions. Also, such concern is not limited to the model only, but bias in the data itself used for training the model might be the origin or somewhere in between.

AI models are susceptible to bias since they learn themselves from data, which here the term "data" is carefully seen as information and statistics gathered for reference or analysis. Said data is not limited to just input features but could include labels, retrieval and sampling methodologies. Therefore, if data reflecting an intrinsically unjust healthcare system is presented to such AI models to learn from, they could unconsciously reinforce pre-existing biases to worse health outcomes for minorities and historically disadvantaged groups . Such biases could arise from systematic misinformation in the model data, such as predicates or demographics, and could result in disproportionate prediction of a test case to a class which leads to disciplinary actions against equitable healthcare delivery. These potentially harmful biases arising from unfair treatment could be amplified by AI models in making predictions. However, due to either the complexity of the model design or black-box prediction mechanism, it remains unclear how such unexpected outcomes are obtained, which aggravates the endocrine effect of such biases.

8.2. Informed Consent and Patient Autonomy
Unless data is properly managed, a patient's most intimate information may not be protected even with steps taken to ensure cybersecurity. In the case of massive hacks, security proved useful only in restoring the health status quo, and information may still flow with different parties, exposing privacy vulnerability. How long will patient information be kept in the database, and should they be informed of its expiry or the timeline of declassification? Even the government or researchers might be clients of healthcare data, and patients usually don't have a say in this regard. Patients also need to consent to the use of their data by second or third parties, particularly AI developers and healthcare companies, otherwise access will be impossible.

Expectation to only protect the data of a hospital cannot fit the healthcare society composed of multiple actors. Nevertheless, one idea that patients lit on is their agency in accessing their healthcare data and performing actions on it. Mechanically, if a decoder is applied to only a portion of molecules, that portion loses anonymity. If the decoder is applied to some patients' information, they would no longer be "model patients" for the algorithms, and vice versa. They must understand this trade-off both beforehand and in the end. This means that healthcare practitioners must be transparent with the patient regarding the capabilities and risks of the AI intervention, ranging from the margin of error to potential unwanted consequences. With consent, healthcare practitioners must process the patient's data as indicated. A consent that automatically allows the deregistration of the patient is inadmissible. New consents that would derive from patients' unprocessable information must be discussed with the patient and considered again. Informed consent thus refers to a broad set of understanding, exchanging, and conversing tasks around this hierarchical decision tree that might involve at least the relatives, the doctors, and their AI advisors.

Consent can be confirmed through either a digital/handwritten signature or through verbal confirmation, which ideally relies on the capability of running the conversation once again at the patient's request. It is also important that AI-automated carriers, such as robots in hospitals, are able to ensure informed consent by a consent-free explanation or a verbal signature. Impossibility to conceive AI systems or to imagine unforeseeable uses of AI for forthcoming patients might diminish the legitimacy of the conformed consent. As AI may moreover affect the consent process itself, milder expectations for an AI system mistakenly drafting consent materials could be considered.

9. Conclusion

Digital transformation in healthcare has led to important innovations in the last decade, compounded by the COVID-19 pandemic. Electronic health records, telemedicine solutions, digital contact tracing applications, and other digital health applications have been extensively deployed. However, the full potential of digitalization and the corresponding data it generates is still untapped.

In order to leverage the full potential of data in healthcare, artificial intelligence and big data analytics need to be adopted and further deployed. AI and BDA offer several new opportunities to derive better and richer insights from electronic health records, telemedicine interventions, and other data sources. Firstly, improved human resource optimization in healthcare delivery can be derived. Secondly, AI can transform and improve telehealth by allowing automatic patient triage and use of patient data for post-consultation analytics. Finally, AI-powered patient health data analytics can allow predictive monitoring to derive real-time monitoring of patients based on their treatment adherence and health vitals.

This text provides an understanding of how healthcare organizations can set up a systematic approach for knowledge-intensive and AI-enabled BDA for enhancing quality healthcare delivery. It highlights strategic choices and non-routine tasks that healthcare organizations face while

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considering revolutionary AI-powered big data analytics in their delivery system. The analysis of interviews with professionals covering the entire healthcare delivery process delineates best-practice solutions, including novel integration mechanisms. The future research directions and systematic frameworks for repurposing the knowledge-intensive processes into a BDA model are also discussed. In summary, AI and big data bring transformative value to the healthcare industry around the world, providing solutions to pandemic-related challenges, improving treatment efficiency, and enhancing overall healthcare.

9.1. Future Trends

The global pandemic and the introduction of 5G networks are currently reshaping healthcare service delivery. Telemedicine is a virtuous way to allow patients and UGs to be present only on the telemedicine site. Using telemedicine technology makes healthcare more accessible by facilitating communication, improving patient outcomes, lowering healthcare costs, and improving the quality of care. On the other hand, the emergence of big data has created an urgent need for tools that can analyze data from various sources to help clinicians detect disease patterns and manage hospital resources. Healthcare organizations are exploring high-speed internet infrastructures and AI and analytics techniques that will enhance their ability to deliver efficient, timely, and data-driven care.

The design and unfolding of precision medicine have made big data more prevalent in healthcare systems. Patients are increasingly encouraged to collect data on their own health status through various wearables and communication devices. These changes require healthcare organizations to rethink their physician-patient communication, data management policies, and business models. In addition to representing a pressing need and interest of relevant actors, these topics address IT and economic issues that fall within the broad boundaries of health databases. Change processes around them impact the quality of care and the way with which patients, healthcare providers, and healthcare companies interact with one another. These topics simultaneously need coherent technical solutions and a non-standard economic approach.

Nevertheless, existing healthcare management models risk becoming obsolete as they cannot process the new forms of big data generated by patients and care delivery organizations. The design of new management models constitutes an urgent research priority. It involves: (i) a comprehensive survey of patient-generated health data and their sources, purposes of collection, processing, and usage across the life cycle, and added data processing requests, as well as an analysis of potential operational issues that may affect the ex-ante and ex-post decision-making process; and (ii) a collection and analysis of currently running initiatives, including co-pay and pricing-based endeavors to contain the problem, as a first step towards the design and implementation of appropriate pricing schemes of the services offered.

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