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Review Article

Harnessing Artificial Intelligence In Healthcare: Advancements, Challenges, And Future

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ABSTRACT

Healthcare has been revolutionized by applications of artificial intelligence (AI). Focusing on the following critical areas, this study draws from a broader literature review that reveals the function of AI in healthcare: (i) diagnostics and imaging in the medical field, (ii) online medical treatment, (iii) pharmaceutical development and research, (iv) patient involvement and adherence, (v) rehabilitation, and (vi) other administrative uses. The use of artificial intelligence (AI) has many practical applications in healthcare. It can detect clinical conditions in imaging and diagnostic services, help control the 2019 coronavirus disease (COVID-19) outbreak through early diagnosis, manage electronic health records, improve patient engagement and treatment plan compliance, reduce administrative workload for healthcare professionals, discover new drugs and vaccines, identify medical prescription errors, store and analyze large amounts of data, and facilitate technology-assisted rehabilitation. Privacy, safety, the right to decide and experiment, costs, information and consent, access, and efficacy are some of the technical, ethical, and social concerns that this scientific presentation addresses as it integrates AI into healthcare. In order to ensure patient safety and hold healthcare providers accountable, as well as to increase adoption and substantial health outcomes, proper governance of AI applications is essential. Accurately resolving regulatory, ethical, and trust concerns while promoting the adoption and use of AI requires effective governance. An AI-driven healthcare revolution has been underway since the COVID-19 pandemic, and this revolt could represent yet another advance in meeting the healthcare demands of the future.

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INTRODUCTION

Healthcare expenditures have grown at an exponential rate, outpacing GDP growth rates, putting health systems around the world in a precarious financial position [1]. With the 2019 coronavirus disease (COVID-19) pandemic and the conflict in Ukraine, this issue became quite clear. There is a confluence of factors, including limited resources, an aging population, an increase in chronic diseases, and the burden on healthcare systems that have historically failed to meet the need for accessible and available services. Furthermore, other nations' health systems are collapsing because to the COVID-19 epidemic, including Indonesia, Brazil, and India [2]. Having its services managed by either a "accountable care organization (ACO)" or a "health maintenance organization (HMO)" highlights a Highly Reliable Organization (HRO), which is crucial for health systems that rely on evidence-based care tactics and strong disease management pathways to meet needs and regulate practices in accordance with industrial healthcare delivery services. [3]. Nevertheless, the prevalence of long-term health conditions in America is on the rise; 60% of individuals deal with at least one chronic illness, and 40% deal with two or more; this results in yearly healthcare expenditures of $3.3 trillion [4]. Furthermore, this scenario drastically altered due to the new viral disease, which was officially named COVID-19 by the World Health Organization on February 11, 2020 [5] after being first identified in Wuhan, China, in 2019. Ever since, the healthcare industry has been experiencing a digital revolution that is going to change a lot of the basic components of medical treatment [6]. Possible cause of this condition: the enormous strain that COVID-19 has put on the world's healthcare systems, supply chains, and healthcare workers. Healthcare stakeholders were also compelled to embrace digital technologies due to the pandemic [7,8]. The healthcare sector underwent significant fundamental adjustments in the aftermath of the pandemic. Increased use of virtual healthcare systems and related digital developments, for example, has led to current-generation consumers' (patients') active engagement in healthcare-related decision making [9]. Nevertheless, insurmountable obstacles can arise; devising methods to conquer them will pave the road for the journey to enter the future of healthcare. New developments in healthcare are driven by patient feedback, experiences, and requirements. Among their primary goals is the global dissemination of patient-centered facilities through the development of digitally enabled physician-patient interactions [10]. Improving medication adherence, monitoring health condition, and providing increased customer satisfaction have all become imperatives that necessitate the use of cutting-edge digital technology [11]. In the time following hospital discharge, these features would be most useful while utilizing digital health platforms. Meanwhile, patients are understandably wary about disclosing personal health information; healthcare organizations (HCOs) aim to alleviate this fear by consistently providing services that are trustworthy, empathetic, and open [11]. Transforming healthcare with new emerging technologies, a different kind of workforce, and different standards of practice are all necessary outcomes of the recent upsurge in biomedical science, which encompasses fields such as genomics, digital medicine, artificial intelligence (AI), and its subset, machine learning (ML). Diagnostics, therapies, care delivery, regenerative treatment, and precision medicine models can all be enhanced and revolutionized by genomics and other technologies, such as biometrics, tissue engineering, and the vaccine industry [12]. You can find the definitions of AI-related terminology in Table 1.

Term	Definition
Artificial intelligence (AI)	Machines programmed with algorithms or rules can learn and solve problems just like humans can; this field is known as artificial intelligence (AI) [13]. Artificial intelligence (AI) is most often used to describe computer systems that can learn and do tasks normally performed by humans, such as reasoning, sensory comprehension, adaptation, deep learning, and engagement [14,15]. The goal is to make it work like the brain. The fast development of analytical techniques and the proliferation of health data are driving this paradigm change in healthcare [16].
Machine learning (ML)	Machine learning (ML) is a branch of artificial intelligence (AI) that tries to make doctors' jobs easier and faster. It also refers to a number of statistical methods that enable computers to learn from their own experiences, independent of human programming. Iterations of algorithms are a common way that algorithms learn new things [17]. The healthcare industry also makes use of it as a tool to better manage clinical data and provide better patient care. It is a branch of artificial intelligence that aims to teach computers to think and learn in the same way as people do [18].
Distributed Ledger Technology (DLT)	Distributed ledger technology (DLT) is a new and quickly expanding way to record and share data across various databases (ledgers) [19]. There is no way to alter it, and it is easily accessible. It has the potential to empower patients with their own data, leading to more confidence in a sector that impacts everyone's lives [20]. Integrating DLT with AI outlines a fresh and cutting-edge approach to accomplish intelligent, robust, and secure treatment of data from electronic health records [21].
Natural language processing (NLP)	By "natural language processing," we mean the academic discipline that studies how computers and humans communicate via language [22]. To make it more accessible to electronic healthcare systems, natural language processing (NLP) methods can extract meaning from unstructured healthcare data, assess its grammar, and translate it. Healthcare quality and cost are both enhanced by these methods [23].
Metaverse	Avatars let users to engage in activities such as playing games, working, and interacting with others in real-time in the metaverse, a 3D realm that is based on VR and AR [24]. Customized to meet patients' needs, it provides a captivating, engaging, and enjoyable healthcare service experience. Artificial intelligence (AI), telepresence, blockchain, VR, AR, and digital twinning are all part of it. A great deal of healthcare is affected by these technologies [25]. Education, research, training, illness prevention and management, and the sole association of the metaverse application with healthcare creates a "niche theme" for academics. As a tool for improving the skills of future doctors, it has grown in popularity. In addition, digital twins, a versatile technology, allow for the direct monitoring of patients' health conditions from the comfort of their own homes and the integration of the real and virtual worlds [26,27].
Chat Generative Pretrained Transformer (ChatGPT)	ChatGPT is an artificial intelligence (AI) conversational agent that can mimic human speech using machine learning and natural language processing (NLP) [28]. Careful examination and resolution of the accompanying legitimate concerns should pave the way for its potentially fruitful use in healthcare practice, teaching, and research. As a chatbot, it understands human language and can generate replies through a text-based interface [29]. Patient assistance, administration and monitoring, and tumor screening, diagnosis, and management were all part of the healthcare chatbot application outlined by Xu et al. [30].

Transformer	Computer vision (CV), natural language processing (NLP), and speech processing are only a few of the many widespread applications of Transformer, a crucial deep learning model [31]. Medical imaging, electronic health records, and the detection of COVID-19 are some of the areas where transformers are used [32–36].

Also, new technological developments that are impacting smart health include artificial intelligence (AI), the metaverse, and data sciences [38]. DHTs also include wearable devices, telehealth, telemedicine, mobile Internet devices (MIDs), and personalized medicine [37]. Improved prevention, earlier diagnosis of deadly diseases, and remote management of chronic diseases away from traditional care sites are all outcomes of these technological advancements. One example is wirelessly observed therapy (WOT), which uses a new approach to tracking patients' adherence to treatment [39]. In this era of revolutionary and minimally invasive medicine, the most encouraging new approach is to provide and transmit health services whenever and wherever they are needed. The receiver of a MID can gain access to useful resources, such as related apps and social media (SM). With MIDs, professionals have access to a plethora of resources, including scholarly databases like Scopus, Medscape, and Web of Science. In contrast, SM networks like YouTube, Facebook, WhatsApp, Wikipedia, and other IMAs can be accessible to both experts and amateurs. In the post-COVID-19 age, such AI-powered digital health modalities are rapidly expanding in the healthcare industry [40]. Since COVID-19 crippled the global healthcare system, artificial intelligence, machine learning, and deep hypertext have driven a revolution in healthcare. For example, the Internet of Things (IoT) is one new technology that AI is currently incorporating into consumer-level DHTs. With the widespread use of AI and ML in healthcare systems, the Internet of Things is anticipated to become the intelligence of things [1]. The utilization of acquired data to modify processes will impact behavior and values [41]. People in general are optimistic about AI-powered intelligent medical technology because it paves the way for patient autonomy through the 4P model of medicine: predictive, preventative, personalized, and participatory [42]. Better, faster, and cheaper healthcare has already resulted from AI integration in healthcare [12].

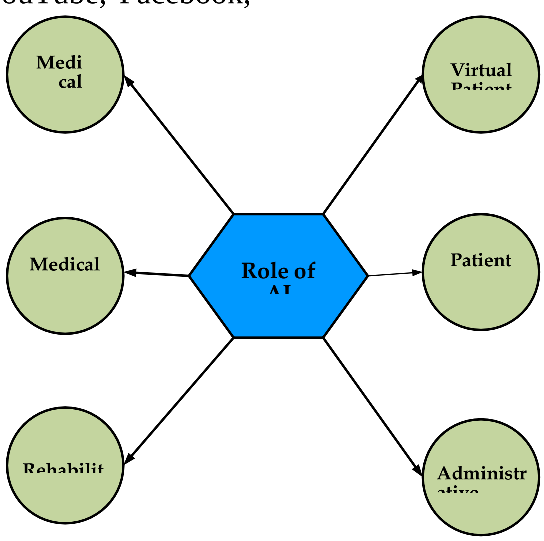

Figure 1. Application of AI in various aspects of healthcare.

Thanks to digital health tools, doctors may access patient records and get a better picture of their patients' health as a whole. Also, doctors can give their patients more data about their health thanks to this. There is legitimate fear that these modalities, especially with the public's and professionals' heavy use of SM and IMAs, could have a more significant psychological influence, but there are also genuine prospects to increase therapeutic outcomes and efficacy [43]. Furthermore, big data is generated by the accumulation of data from various sources, including wearable devices, telemedicine, mHealth, telehealth, MIDs, and other medical technologies powered by artificial intelligence [44]. This data is used to speed up the application of machine learning and artificial intelligence in health systems by learning from research data, user experience, and the examination of large datasets [45]. Moreover, EHRs include a wide range of patient healthcare data. Innovative AI technology can link these health statistics, allowing for more precise insights into patient care. One other area where AI has become popular is in healthcare's use of big data [46]. In addition, by enhancing EHRs with analytical algorithms, healthcare practitioners can boost clinical services with big data analytics [47]. Improved data analysis is another benefit of these analytics, which employ AI advancements to filter huge data on multiple grounds [48]. Given the extensive utilization of AI in healthcare, this research seeks to shed light on its function in the industry by examining the following critical components (Figure 1): (i) diagnostics and imaging in the medical field, (ii) online medical treatment, (iii) pharmaceutical development and research, (iv) patient involvement and adherence, (v) rehabilitation, and (vi) other administrative uses. Furthermore, the writers discuss certain difficulties associated with healthcare AI. To further advance the advantages of AI tools in healthcare, these results supplement the current research.

Artificial Intelligence's Place in Healthcare

Medical Imaging and Diagnostic Services

Radiology practitioners are using AI more and more to reduce diagnostic errors in the context of prevention and to diagnose various diseases early. AI is a great tool for image processing. Similar to this, AI is a clever and useful tool for evaluating echocardiogram and ECG charts, which cardiologists utilize to help them make decisions. The Ultromics platform uses artificial intelligence (AI) to analyze echocardiogram scans, which sense heartbeat patterns and identify ischemic heart disease [49]. It was reported to be used in an Oxford hospital. Using body imaging modalities, AI has shown promising results in the early diagnosis of conditions like skin and breast cancer, eye disease, and pneumonia [50–52]. Artificial intelligence (AI) techniques identify and screen for neurological conditions including Parkinson's disease, as well as analyze speech patterns to predict the onset of psychosis [53, 54]. A recent study used ML models to forecast when diabetes will manifest. The best model to predict the various diabetes factors, according to the results, was a two-class augmented decision tree [55]. Moreover, Gudigar et al. [56] reported that the use of AI approaches in a number of medical imaging instruments, such as computed tomography (CT), ultrasonography (US), and X-rays, has greatly contributed to the fight against COVID-19 by facilitating early diagnosis. According to their findings, COVID-19 cases could be predicted using deep neural networks (DNN), hybrid approaches, and handmade feature learning (HCFL). The use of CT scans, MRIs, X-rays, and ultrasound in the diagnosis of COVID-19 was also thoroughly described in a recent study. It claimed that AI has been crucial in assisting the general people in battling the feared virus [57]. Furthermore, registration, detection, classification, image-to-image translation, segmentation, and video-based applications are all performed in medical imaging analysis using a deep learning model called Transformer [34]. According to earlier research, transformers may be used to distinguish COVID-19 from pneumonia on X-ray and CT images, which is a critical need for meeting the short turnaround time needed to handle COVID-19 cases [58,59]. Using inputs like patches of chest X-ray pictures, another study used the ImageNet-pretrained vision transformer (ViT)-B/32 network to detect COVID-19 [60]. A new hybrid chest CT-built approach for automatically detecting COVID-19 was proposed in a study by Wang et al. [61]. It is a suggested three-segment biogeography-grounded optimization (3SBBO) method and wavelet Renyi entropy (WRE) based computer vision-based diagnosis technique. It consists of the 3SBBO algorithm, a feedforward neural network (FNN), and WRE. The images are classified by the FNN after the 3SBBO improves the network's weights and biases and the WRE extracts image features. In the detection of COVID-19, our approach outperformed radial basis function neural networks, extreme learning machines with bat algorithms, and kernel-based extreme learning machines. Furthermore, according to Gheflati et al. [62], the ViT is utilized to classify breast tissues into benign, malignant, and normal categories using ultrasound (US) pictures. Compared to convolutional neural networks, it demonstrated superior performance in the classification of US breast pictures (CNNs). Moreover, artificial intelligence (AI) includes the use of deep learning methods such as Generative Adversarial Networks (GANs), or artificial neural networks, which have an impact on radiology. GANs are composed of two artificial neural networks: (i) a discriminator that identifies the difference between synthetic and real images, and (ii) a generator that creates images that resemble genuine ones. In terms of radiology, the generative model is able to reproduce the training images and create new images using the characteristics of the training photos. The discriminant model is trained to identify different aspects of the images, such as whether or not pneumonia is visible on a radiograph. The generator model trained in conjunction with the discriminator model was found to be able to lead to advancements in radiological activities, including cross-domain image synthesis, aberrant detection, and image synthesis [63]. Expert radiologists had difficulty differentiating between real images and GAN-generated images of lung cancer lesions [64]. GANs also present a fantastic chance to advance medical research and teaching. They provide simulations and training materials for students in a timely manner. For example, examples of each type could be created and shown to students who struggle to distinguish between "lower lobe collapse" and "consolidation." Thus, by providing edge-case learning materials, synthetic data can aid in the education of students. Additionally, by modeling placebo groups based on historical data, synthetic control arms have been created, which eliminates the need for a real-life placebo group. This lowers expenses and increases the number of treatment arms in clinical trials [65]. Furthermore, the public uses ChatGPT, a deep learning-based large language model, to provide medical advice; as a result, it has become a cause for concern. The public may be tempted to utilize such a model in place of expert medical guidance in order to get treatment recommendations or make potential diagnoses based on clinical aspects [66]. About one-third of adults needed Internet-based medical guidance in order to self-diagnose, according to a prior US survey. Approximately half of them then sought medical advice regarding the results obtained from the Internet [67]. Apart from this, a metaverse of "medical technology and AI" (MeTAI) supports AI-based medical practice, namely medical imaging-guided diagnosis and therapy. "Virtual comparative scanning," "raw data sharing," "augmented regulatory science," and "metaversed medical intervention" are some of the crucial uses for MeTAI. The following describes a model execution of the MeTAI ecosystem: Prior to the patient having a real CT scan, the optimal imaging result is determined by simulating the patient's scans with virtual machines. This information is used to create an actual scan. After getting the patient's consent, the meta-verse photos are then distributed to the patient's medical team. The medical researchers receive access to the tomographic raw data and images after following security protocols. Augmented clinical trials can make use of real and virtual image collections, data, and other medical evidence that can be integrated into the metaverse. Finally, if therapeutically recommended, the patient is followed up in the metaverse for rehabilitation after experiencing a metaverse-assisted remote robotic procedure. Nevertheless, MeTAI faces difficulties with privacy, investment, inequality, and security [68]. Furthermore, medical scans are collected in a methodical manner, stored for a while, and made publicly available for AI system training [69]. These AI systems might shorten the time and expense required to review medical scans and perhaps enable the taking of more scans for more effective targeted management [70]. AI is having an effect on illness diagnosis and clinical decision-making as well. For the purpose of diagnosing diseases and making clinical decisions, it has the ability to process, analyze, and report vast amounts of data using various modalities. In therapeutic zones, it can help doctors make better clinical decisions or possibly take the place of human judgment [71]. Additionally, studies that make use of computer-aided diagnostics have demonstrated exceptional specificity, accuracy, and sensitivity in identifying small radiographic aberrations, which has the potential to improve public health. However, lesion detection is often used to characterize outcome assessment in AI imaging studies, excluding factors such as lesion kind and biological severity that could distort the results of the AI. Furthermore, by using radiological and pathological endpoints unrelated to the patient, the predicted sensitivity may be raised, but at the expense of an increase in false positives and potential overdiagnosis due to the detection of minute anomalies that could be mistaken for subclinical disease [72].

Virtual Patient Care

According to Baig et al. [73], research has previously been done on the possible applications of ML and AI in healthcare as well as the development of wearable technology. As a result, active and reasonable wearable technology solutions for virtual patient monitoring and management have grown commonplace and are now included in care standards. Additionally, by utilizing wearable, non-invasive sensors, AI helps manage chronic conditions like diabetes mellitus, hypertension, sleep apnea, and chronic bronchial asthma. [74]. A smart sensor system built on a combined sensor network was suggested by a prior study as a way to monitor a person's surroundings and house and gather information about their behavior and health. Wearable, biological, and inconspicuous sensors are part of the suggested platform. These sensors keep an eye on physiological parameters like blood pressure, ECG, breathing waveform, pulse rate, and respiratory rate. It has been suggested that a smart device, like a tablet, serve as an interface between the user and the sensors. Moreover, the gathered data are uploaded to the cloud for data analysis and storage related to senior care. [75]. A woman with atrial fibrillation was positively identified as the likely cause of her stroke after a thorough negative evaluation, according to a case report by Patel and Tarakji [76]. The patient was advised against utilizing a wearable digital device to capture ECG signals. Those recorded signals were later validated by her electrophysiologist. As a result, consumer wearable digital devices facilitate accurate diagnosis. In reference to mental health diseases, Sukei et al. [77] demonstrated that machine learning (ML) models capable of handling heterogeneous data with significant missing information may be constructed to predict emotional states using mobile sensor data. Medical professionals may find these models to be useful in evaluating patients' emotional states. Finding a solution for sparse and missing tagged data is advised in order to free up time in the future to concentrate on creating more creative models. Ever since the COVID-19 pandemic was brought on by the widespread prevalence of SARS-CoV-2, wearable technology has advanced to the point where wearables can now record physiological changes in biometrics or even transmit online active patient monitoring [78]. In addition, real-time wearable research on COVID-19 cases will help to better understand the clinical features that users overlook but that laboratory investigations support. Bogu and Snyder [79] proposed that wearable sensor data could be used as indicators for the early prediction of COVID-19. Artificial intelligence (AI) can diagnose SARS-CoV-2 infection in solid organ transplantation and can help predict the course of specific diseases, such as diabetic nephropathy, by utilizing predictive modules with machine learning and large data [80]. Yu et al. [81] examined interactions in upcoming AI-enabled applications for point-of-care use in such occurrences and stressed the significance of incorporating AI into bedside care in COVID-19 and the impending pandemic. The COVID-19 epidemic has further increased the need for remote healthcare services. Compared to standard videoconferencing-based telemedicine apps, metaverse applications have the potential to provide a superior experience [82]. According to a recent study, during COVID-19, telemedicine growth and metaverse development rose 38-fold [68]. The reduction in in-person consultations and the management of the virus's potential to spread during the COVID-19 pandemic may have contributed to this increase [83,84]. It also demonstrated the potential for new metaverse capabilities, such as raw data sharing and virtual comparative scanning, which would be reliable, affordable, and simple to use [68]. Furthermore, metaverse systems might make use of augmented reality (AR) glasses, which would allow users to watch live audio chats and videotapes and communicate with clinicians in real time. In order to provide remote physicians with timely, efficient, and on-the-spot management, augmented reality (AR) technologies would enable users to connect directly and provide a live flow of emergency conditions [85]. Utilizing modern technologies like artificial intelligence (AI), telepresence, blockchain, virtual reality (VR), augmented reality (AR), and digital twinning gives healthcare providers access to creative ways to deliver low-cost management that enhances patient outcomes. Through the use of the Internet, the metaverse creates a virtual environment where human emotions and movements are mimicked. It includes the social and economical structures of actual and virtual worlds in their entirety [86]. AI may also help strengthen the metaverse's structure, which would improve virtual worlds' core functions and 3D immersive experience [87]. HCPs can monitor, examine, and report patient symptoms while they are not in the conventional location thanks to remote patient monitoring (RPM), a subset of telehealth. By utilizing sensors and communication technology, RPM optimizes the performance of medical interventions. Examining patient issues or health data remotely is made simpler by it. Additionally, it enables patients to participate and acknowledge their state of health [88]. The efficiency of HCPs' time management, which is dependent on their workload, is what makes traditional patient-monitoring frameworks reliable. This kind of surveillance also uses intrusive techniques that need skin-to-skin contact to check for health issues. The integration of wearable technology, telehealth applications, and contact-based sensors is how new IoT techniques are used in healthcare to achieve RPM. It is frequently used to check vital signs or other physiological factors, like the ability to recognize motion, which can aid in medical decision-making or therapy plans for conditions like movement disorders and psychological problems [89]. Furthermore, during the COVID epidemic, healthcare providers made use of RPM systems to help maintain patient care continuity. A recent study assessed the CareSimple COVID platform and the Telecare COVID platform, two remote patient monitoring systems, for COVID-19 patient monitoring. Patients with COVID-19 were said to have reacted favorably to these two platforms, with little notable differences in the experiences of these patients. It is advised to think about making use of these platforms during the post-hospitalization and post-pandemic phases [90]. When it comes to RPM applications, traditional machine learning and deep learning are popular AI technologies that are utilized to detect and predict vital signs as well as categorize patients' movements. AI-driven RPM designs have revolutionized healthcare monitoring applications by enabling early patient deterioration detection, federated learning to personalize patient health variable monitoring, and reinforcement learning to absorb patient behavior patterns. RPM facilities can be revolutionized by AI, but there are a number of obstacles to overcome, including those related to privacy, signal processing, data volume, uncertainty, imbalanced datasets, feature extraction, and explainability [89]. In addition, OpenAI created the AI language model ChatGPT. It works as a more precise AI-powered chatbot that can reply to user inquiries and comprehend natural language exchanges. The chatbot powered by ChatGPT provides details on a specific medical condition or treatment plan. In multiple languages, it provides accurate and up-to-date answers to the patient's inquiries about their clinical characteristics, prescribed medications, and therapeutic procedures. It provides HCPs with an overview of patients' medical records and could help them carry out RPM to maintain patient health. It also serves as a reminder for patients to monitor their vital signs so they may notify healthcare professionals of any unusual changes. It enables patients to schedule doctor appointments [91]. Similarly to a virtual assistant that reminds patients to follow their prescription and provides information about their health, ChatGPT may also respond to a computer software that assists patients in managing their treatment. One example of ChatGPT's use in medicine is the rise of virtual aides for patients. When a patient has the flu or a cold, a virtual assistant can provide advice on managing a chronic illness like diabetes or provide over-the-counter or DIY medications. Virtual assistants can be accessed through digital platforms like websites, voice assistants, and mobile applications. Nevertheless, there are many drawbacks to ChatGPT in the medical field, including concerns about medical ethics, data interpretation, privacy, security, permission, and liability [91]. Conversely, a drawback of implemented Wearable Patient Monitoring (WPM) systems is data connectivity; in these systems, patients are monitored through low-range Bluetooth devices while confined to fixed locations. End-user acceptability is another important component of WPM systems. It depends on patient and physician acceptability as well as user awareness. When utilizing mobile data for communication across time and for various data collecting purposes, cost concerns may surface [73].

Medical Research and Drug Discovery

The vast and intricate datasets employed in medical research are perfectly suited for analysis by AI [92]. It can also be used to find scientific research projects, combine different kinds of data, and encourage the development of new drugs [93]. AI is being used by pharmaceutical companies to expedite the medication development process. Predictive analytics is a tool that scientists can use to identify suitable candidates for clinical trials and create precise models of biological processes [92]. In the pre-trial stage of clinical trials, machine learning (ML) helps with participant organization, cohort selection, data collection, and analysis. It can improve clinical studies' success, generalizability, efficacy, and patient-oriented perspective. But more attention has to be paid to ML's conceptual and functional roadblocks in clinical studies. Natural language processing (NLP), in addition to machine learning (ML), has shown promise in a number of ways for improving participant management in clinical trials. Nevertheless, it is unclear how these tools will affect the standard of clinical trials and the experience of participants. To enhance participant management, more study comparing various approaches might be done [94]. Generative artificial intelligence (AI) can produce synthetic data in clinical research to improve datasets and boost diversity [65]. Furthermore, researchers can use metaverse applications to conduct studies in a controlled and immersive environment. Applying the metaverse has the advantage of facilitating research collaboration between scholars who are geographically separated. They can conduct joint study in a virtual environment that is comparable to that of researchers in the same room thanks to the metaverse [95]. ChatGPT, an additional AI-powered tool, can help with data collecting and provide information on clinical trials in the context of clinical trials [91]. It can assist in distilling relevant literature and identifying noteworthy findings, enabling medical researchers to adeptly explore vast amounts of Internet-based data [96]. Furthermore, a chatbot that uses ChatGPT helps medical researchers by translating medical terms. However, employing chatbots in medical research may raise additional ethical concerns [91]. Furthermore, ML, bioinformatics, and cheminformatics models have paved the way for the development of AI technologies in drug discovery [97]. The lengthy and expensive process of finding novel drugs can be significantly shortened by these technologies [98]. According to a previous study, Eve, an AI-based robot scientist, completed the medication development process quickly and affordably [99]. AI is mostly employed in drug discovery to find candidate molecules, but it's likely that in the future it will be used dynamically in drug discovery [98]. Numerous AI-powered drug discovery triumphs demonstrate how quickly medication candidates can be investigated by companies with AI integrated. To manage a unique, inherited type of Wilsons disease, for example, Toronto-based deep genomics developed a new genetic target and the corresponding oligonucleotide therapeutic candidate, DG12P1 [97]. Additionally, in order to develop novel first-in-class clinical medications, it is critical to identify new therapeutic targets during the drug discovery research process [97]. Artificial intelligence (AI) has the ability to identify hit and lead compounds, provide quick drug target authentication, and improve drug structure design strategy [100,101]. AI's capacity to predict how a drug would interact with its target has also been used to help with drug repurposing and avoid polypharmacology. Repurposing an existing medication advances it to later stages of clinical testing [100]. According to earlier research, ChatGPT may be used to evaluate a substantial corpus of scientific material, including research articles and patents, which could lead to the identification of novel therapeutic targets and the generation of creative ideas. Before the model is used to produce assumptions or recommendations for additional study, it helps train the model on a vast amount of scientific data in the case of medication development [102,103]. AI is also utilized for drug screening, other from this [104]. According to earlier research, a variety of algorithms, including nearest-neighbor classifiers, DNNs, RF, SVMs, and extreme learning machines, are used for both in vivo toxicity and activity forecasting and virtual screening (VS) based on synthesis viability [105,106]. AI is notably used in the examination of the spike proteins that make up a virus in the process of developing vaccines. Using an AI system, it is possible to classify many components in a complex structure and identify the one that most likely triggers a strong immune response [107]. Moreover, the development of AI systems in healthcare fosters the creation of novel COVID-19 viral genotypes and variations. In order to obtain active healing and preventive agents for containing the COVID-19 pandemic, it also helps in the development of vaccines and medications (including drug repurposing) [108].

Patient Engagement and Compliance

When it comes to healthcare, the "last stretch" problem is patient involvement and compliance, which ultimately determines whether patients have good or bad health results. Patients are considered to be non-compliant when they do not adhere to their prescribed treatment plans or take their medications as prescribed. Health outcomes, including healthcare use, cost, and patient experience, are likely to improve when patients actively participate in their treatment [109]. Less than half of patients were very involved in their treatment plans, according to a poll of healthcare executives and leaders [110]. Treatment strategies to improve acute or chronic health are developed by healthcare providers using their clinical skills. However, in most cases, it is insignificant when a patient fails to make the necessary behavioral adjustments, such as maintaining a healthy weight, making an appointment for a follow-up, and following a treatment regimen [109]. Under these circumstances, the use of AI to improve patient engagement became more important. ML and workflow engines are increasingly being used to power care spectrum interventions and composites [111]. A promising area of study is the development of timely behavior-inducing messaging alarms and relevant, personalized content [109]. In addition, research shows that engagement rates can be increased by 60% or more by using apps and online portals that allow patients to communicate with HCPs. On the cloud, health-care apps store, retrieve, and disseminate patient records. In addition to improving health outcomes for patients, these apps give users the freedom to access data whenever and wherever they like. These apps allow people to get non-emergency medical information through consultations powered by artificial intelligence. Some applications may now notify users when they need to take their medication and even follow up with them afterward [112]. In addition, ChatGPT is being used in a number of healthcare applications to automate labor-intensive processes, such as creating reports, summaries, and notes. It helps patients with self-management of chronic diseases, medication management, appointment scheduling, and symptom checks [91].

Rehabilitation

AI is revolutionizing the world of rehabilitation with its new applications. The concept encompasses both the real world (robotics) and the abstract (informatics). Another branch of AI, machine learning (ML) describes exact techniques for developing systems that innately get better with use. Uses of ML in rehabilitation include perioperative medicine, myoelectric control, symbiotic neuroprosthetics, brain-computer interface technologies, and many more. In the realm of the musculoskeletal system, ML techniques have found use in areas such as diagnostic imaging, clinical decision support, and patient data interpretation. Using machine signals, a therapeutic artificial cognitive application evaluated rehabilitation workouts [113]. Innovations in artificial intelligence and robots are changing the way rehabilitation studies and treatments are conducted. For instance, smart homes have the ability to notify caretakers when help is required and even aid inhabitants with their everyday tasks. More than that, there are smart mobile and wearable devices that can gather data and give users information to evaluate health improvement and monitor progress toward individual rehabilitation objectives [114]. Also, people can use the inertial sensors in their wearable gear to see if they are exercising correctly and consistently [115]. Regular people used Apple iWatches to track how well they adhered to a rotator cuff exercise program. The workout accuracy of all algorithms was correctly categorized using a number of supervised learning approaches [116]. Wearables and ML have the ability to revolutionize activity tracking, as shown by a neural network that attained 99.4 percent detection accuracy. Wearable performance monitoring may not be enough to improve adherence due to the various barriers to adherence associated with exercise efficacy [117,118]. Robots that are both physically and socially helpful can also aid in the healing process when a person has been sick or injured. Losses in motor control, sensory perception, or cognition can also be bridged with the help of these robots. Improving people's functional capacity, independence, and health is a key purpose of these devices [114]. Simple mobilization with dexterous or soft robotic hands was used to treat patients with musculoskeletal disorders. But it hasn't been proven that this treatment works in the long run [119]. In the future, patients may be able to rely on AI-enabled robots to assist them in performing actions more efficiently, according to a recent study [120]. By incorporating ChatGPT, an AI-driven technology, into rehabilitation sessions, HCPs could bridge the gap between the demand for rehabilitation services and the availability of qualified therapists, according to Frackiewicz [121]. In addition to traditional treatment, they can provide patients an AI-driven alternative. Patient engagement and interest are maintained throughout the healing process with the use of ChatGPT, which offers personalized and collaborative help. ChatGPT can be set up to provide workout suggestions, track recovery progress, and provide feedback to people who have suffered physical ailments. On top of that, it can help those who have suffered a brain damage or stroke practice speaking and language abilities through engaging in conversation. No matter where you are, you can use your digital device to access this tool. A recent study found that ChatGPT and similar language models were trained to rewrite text with a strong emphasis on empathy. It enhances conversational abilities for those who aren't experts and makes it easy to communicate in a system that helps those with mental health issues. Cognitive behavioral therapy is one community-based activity that relies on self- or peer-managed therapy, and this article highlights the potential of human-AI partnerships to enhance this process [122]. Metaverse neurorehabilitation also includes evaluations of movement based on deep learning, virtual character movement employing weight shift, an artificial intelligence-based gross motor function categorization system (GMFCS), and rehabilitation materials as a reward during rehabilitation. The goals are to reduce the likelihood of COVID-19 transmission, increase interest and enjoyment, and provide remedial exercises using AI [123,124]. Metaverse physiotherapy (MPT) improved cardiopulmonary and gross motor performance and decreased perceived COVID-19 infection in children with CP, according to a recent study [125]. Computers can automate the detection of gait abnormalities and accompanying pathologies in patients with osteoarthritis and Parkinson’s disease, according to ML-driven video analysis, which further proves the applicability of AI in gait analysis [126]. With the help of digital therapists' guidance and advice, real-time monitoring, and remote tracking, home physiotherapy can be effectively provided [120]. To help stroke patients continue treatment outside of hospitals, Lambercy et al. [127] proposed a method for providing remote neurorehabilitation through digital treatments like minimally supervised aided therapy. Since patients are educated at home using the devices, it is important that AI-embedded technologies for remote neurorehabilitation meet the technological needs, which include utility, safety, and robustness. Implementing these technologies in neurorehabilitation necessitates a clinically driven strategy that is open and honest with patients, their families, and healthcare providers; furthermore, these technologies should be scalable. Confidence in home-based, technology-enhanced therapy may improve under these circumstances. Furthermore, it is essential to have all of these qualities in order to get patients with neurological illnesses to agree to rehabilitation using technology and to actively participate in treatment [128]. By making high-quality, sustained, and high-dose therapy widely available, technology-assisted home rehabilitation had a significant influence on neurorehabilitation during and after the COVID-19 pandemic. This, in turn, improved stroke patients' independence, quality of life, and long-term functional outcomes [127]. The use of artificial intelligence (AI) into wearable devices has great promise in the field of sports medicine, according to a recent analysis. In order to help athletes enhance their performance, artificial intelligence systems could analyze sensor data to detect trends in physiological parameters, together with location and kinematic data. Artificial intelligence has the potential to enhance injury prediction models, improve the accuracy of risk stratification systems' diagnostics, offer a dependable method for constantly tracking patients' health data, and generally make patients' experiences better. Wearable technologies may face a number of obstacles that prevent AI from being widely used, despite its usefulness in sports medicine [129]. Among these difficulties is the difficulty of collecting high-quality data with wearable technology, as well as issues with missing data, socioeconomic bias, data security, outliers, and signal noise [129,130]. Artifacts caused by arm motions during physical activity can be detected by heart rate monitors, for instance: In such a scenario, sophisticated sensors could gather and provide only accurate data [129]. The issue of patient acceptance is another important hurdle to their implementation. Half of consumers who owned a wearable gadget ceased using it after six months, according to previous studies [131,132]. One-third of those people had experienced this situation even sooner. Previous research found that whereas 11% of patients thought that wearable equipment utilizing AI was detrimental, 50% of patients saw it as a major opportunity. The human element of healthcare was a major concern for patients who were worried that technology could abuse and profit from their personal information. Consequently, in order to increase patients' acceptance and use of AI, it is necessary to educate them about how AI helps physicians, as well as their own strengths and weaknesses [133].

Administrative Applications

Automated data retrieval from historical medical records, structured data regions in therapy notes, and documented patient contacts are just a few ways in which AI is easing administrative costs [134]. As an example, administrative and regulatory tasks account for one-fourth of the typical American nurse's shift [135]. The use of voice texting could free up time for nurses and doctors [134]. There are further algorithmic methods based on ML that are more accurate, however rule-based systems coupled with EHR systems are still widely utilized [110]. According to Wang et al. [68], Amazon is developing a novel ML solution to mine unstructured electronic health record data and research notes for useful information. In addition, BEHRT, a model for EHRs based on deep neural sequence transduction, was described by Li et al. [32]. The BEHRT demonstrated the efficacy of utilizing different embeddings—including age, position, visit, and event—to describe the patient's medical background. In a person's future visits, it may simultaneously predict the likelihood of 301 conditions. When compared to current deep EHR models, it considerably raises average precision scores across a range of activities. Its elastic structure allows it to incorporate diverse, heterogeneous ideas like evaluation, diagnosis, and medications, which improves the precision of its forecasts. A hierarchical BEHRT (Hi-BEHRT) model, which is built on hierarchical transformers, was suggested in a recent study as a means of risk prediction. For patients with a lengthy medical history of diabetes, heart failure, stroke, and chronic renal disease, the study found that Hi-BEHRT performed significantly better than current deep-learning models on risk prediction tasks [35]. It is interesting to note that RPA can be utilized for a variety of healthcare-related tasks. Clinical records, claims processing, revenue cycle administration, and medical record management are all part of these responsibilities [136]. Other areas where healthcare institutions have implemented chatbots include telehealth, mental health, and patient interfaces. These natural language processing (NLP) techniques can be useful for basic transactions like appointment scheduling and medication refills [137]. Machine learning (ML) is another artificial intelligence (AI) tool that may be used to match data across several websites in the context of payment administration and claims [134]. The accuracy of several claims is checked by insurance organizations. There is a substantial amount of money that might be recovered through data reconciliation and claim inspection if inappropriate claims are caught early enough [109]. Also, a hybrid ML-based decision support system (ML rule-based expert system) was found to be noticeably more accurate in detecting prescribing errors in a clinical environment by Corny et al. [138]. Recent research on AI tool creation for clinical pharmaceutical services indicated heavy use of ML techniques and subsets, especially natural language processing (NLP) and deep learning. Clinical pharmaceutical services will soon see an influx of AI-based applications and solutions, according to the report's conclusion. Together with data experts, we need to move quickly to determine if these AI techniques are useful for clinical pharmaceutical services in the actual world. Pharmacists should be aware of these benefits so they can use them appropriately while still fostering positive connections with patients and other members of the healthcare team [139].

Challenges Faced by AI Utilization in Healthcare

Ethical and Social Challenges

Several ethical and social disputes raised by AI overlap with those raised by high reliance on technology; automation; data usage and issues arising from the usefulness of ‘telehealth’ and assistive technologies, as the effectiveness of AI increases ethical concerns, including the issue of accountability when AI is used in decision making; the ability of AI to make erroneous judgments; AI yield authentication issues; the confirmation of the protection of sensitive data; intrinsic biases in the data used in AI system tests; maintaining public confidence in the growth and benefits of AI systems; influencing the sense of dignity and social isolation of the public in care settings; implications for HCPs' roles and skill requirements; and the ability of AI to be used for malicious activity. Concerns over the dependability and safety of AI-powered healthcare decisions, equipment controls, and therapy delivery have been voiced. There is a risk that AI may make mistakes—some of which might be difficult to detect—or unforeseen consequences, the latter of which could have serious consequences [69]. As an example, AI software that was meant to predict pneumonia-related complications actually advised doctors to reject asthma patients because it failed to take crucial data into account [140]. Concerning transparency and accountability, concerns arise about the accountability of AI decision-makers and the utilization of compensation by individuals affected by AI. Issues with authenticating AI output and detecting mistake or data bias arise, especially with ML technologies, which can be opaque due to their strategy of constantly examining their own constraints and norms as they learn [69]. Explainability is another big obstacle for AI when thinking about its practical uses. The "Explainable Artificial Intelligence" (XAI) subfield of AI is attempting to solve the issue of low AI adoption in decision-critical settings by improving people's ability to understand and use these systems [141]. Also, the logic behind AI is frequently murky and beyond the comprehension of humans. Therefore, humans might find it challenging to trust and comprehend AI findings. One solution to these issues is XAI, which explains how AI works in a way that humans can comprehend and trust [142]. Here we have a group of techniques that can understand and depend on the output of ML algorithms [143]. Providers and patients alike can benefit from XAI's ability to explain diagnostic rationale because AI can now do just that [142]. A recent study found that XAI increases users' trust in AI by graphically displaying the model's forecast and the parameters that were most important in generating it [144]. Another study found that radiologists need a lot of visual information about the automated workflow before they can trust XAI systems to classify CT images [145]. In addition, problems with digital data collecting or data shortages could make AI perform poorly. People with uncommon medical conditions or those who are underrepresented in clinical trials may be affected by this status [69]. Even while they can reduce human mistake and prejudice, data biases can be replicated and strengthened by AI systems during training [146]. The use of such data to train AI runs the risk of producing biased results that reflect societal biases more broadly [70]. The use of sensitive and private data constrained by legal panels presents additional privacy and security concerns for healthcare applications. While artificial intelligence (AI) has many potential uses, such as identifying cyber assaults and safeguarding healthcare computers, it also carries the risk of being hacked to access sensitive data or spammed with biased or incorrect information in an undetectable way [69]. Concerns about privacy, safety, security, cost, information and consent, access, and efficacy are among those raised by Sunarti et al. [147] in relation to clinical AI applications. This is why, prior to incorporating AI into healthcare systems, important medical-ethical values including beneficence, autonomy, equity, and non-maleficence should be promoted [148].

Governance Challenges

The need for effective governance to address regulatory, ethical, and trust concerns is growing in tandem with the use of artificial intelligence (AI) in healthcare [149,150]. Implementing and using AI correctly is an opportunity for active governance at the hospital level to solve these concerns [151]. For healthcare accountability and patient safety, a new study concluded that healthcare system-level regulation of AI technologies is crucial. Also, with this kind of leadership, clinicians have more faith, it's easier to accept, and major health benefits are within reach. In order to deploy AI-powered apps while addressing issues in the clinical, operational, and leadership domains, the governance framework should be comprehensive [152]. Artificial intelligence (AI) also has potential uses in healthcare, research, and personal data protection—all of which necessitate regulations. The commercial and rapid development of AI, however, poses a threat to the established frameworks [70]. Therefore, in order to implement AI-controlled healthcare applications in accordance with medical ethics principles, national and international rules are necessary. Consequently, in 2018, the EU established the General Data Protection Regulation (GDPR) to regulate AI. Data processors and controllers recognized inside the EU are protected by GDPR. It serves as the cornerstone of crucial changes in Canada and the US [153]. In order to mitigate a number of concerns raised by the widespread use of AI, the European Commission recently drafted the AIA. The goal of these rules is to promote the widespread use of AI while simultaneously preventing or reducing negative consequences associated with certain technological applications. To ensure they fulfill all requirements of AIA, high-risk AI systems would be required to undergo post-market observational study and pre-deployment conformity assessments under the proposed law [154].

Technical Challenges

Ai systems use data inputs and produce results in a manner analogous to the human brain. Nonetheless, HCPs are in the dark regarding the metrics used and the reasoning behind an AI system's output; all they can do is In order for healthcare providers to effectively operate AI models, it is technically necessary for them to have basic features and functions [155]. However, there are a few challenges to implementing AI in healthcare. These include the high expense of data validation, the increased costs of storing and backing up data for research, and the inability to develop and maintain IT infrastructure to support the AI process [156]. Along with bias, brittleness (the propensity to be easily misled), and inapplicability outside of the training area are some of the other potential drawbacks of AI algorithms [157]. Changes to datasets, using random matching of confounders instead of real signals, the frequency of unintended biases in clinical practice, making algorithms interpretable, creating trustworthy confidence measures for the model, and testing generalization to other populations are all important considerations [158]. Cost, technical infrastructure, and HCP use of AI systems are all important considerations, thus healthcare providers should devise and execute a sound strategy for AI implementation in healthcare. Another important barrier to widespread adoption of AI-grounded clinical decision support systems is the widespread mistrust or lack of understanding among HCPs regarding these systems due to the unknown risks they may provide. Under these conditions, XAI solutions are prioritized to increase end-user confidence and counteract the lack of AI adoption [144]. Also, physicians' views on AI's utility in healthcare were affected by variables like workload, trustworthiness and hazards of AI, and openness to AI training (Choudhury and Asan [159]). Another thing that people think is holding AI to account is a real problem. The safe use of AI in the future depends on its incorporation into medical and nursing school curricula. understand what the end result is. The term for this difficulty in AI systems is the "black box problem" [160]. Consequently, it is advised to create regulations and safeguards to safeguard physicians and AI in healthcare, as holding them responsible for AI mistakes could impede AI adoption. This also highlights the importance of enhancing the risk perception and performance expectations of AI among healthcare professionals. The presentation of information through an AI interface must be both easy to use and relevant to clinical practice. Before creating and marketing AI in healthcare, it is important to engage all stakeholders, including payers, patients, and providers, and gain a better understanding of clinical demands.

Disadvantages of AI in Healthcare

In order for deep learning and machine learning models to classify or predict different jobs correctly, massive datasets are required. However, data accessibility is a complex issue in the healthcare industry due to the secrecy of patient records and the common reluctance of HCOs to provide patient information. Furthermore, data are not easily accessible after an algorithm has used them for the first time. It is challenging to achieve this situation owing to internal corporate resistance [161], but ML-based systems can continuously develop as more data is added to their training set. Data security and privacy are additional concerns brought up by AI-powered applications. During data breaches, hackers often target sensitive medical records because of their importance and susceptibility to compromise. The secrecy of medical records is, therefore, of the utmost importance [162]. Furthermore, overfitting happens when the algorithm internalizes the relationships between patient attributes and outcomes. This issue arises because the algorithm makes incorrect predictions because of the many variables that impact the outcomes. When AI algorithms achieve better prediction accuracy, data leakage occurs, which means that they may forecast occurrences outside of the diminished training dataset [163-165]. In addition, deep learning algorithms do a poor job of providing meaningful context for the predictions they make. When suggestions go awry, an algorithm has a hard time safeguarding itself legally. Because of this, it's hard for professionals to understand the connections between the data and their predictions. The public may lose trust in healthcare systems due to the black-box problem in AI technologies [166]. Some in the healthcare industry may be afraid that artificial intelligence may eventually displace them or at least cut into their job opportunities. Concurrently, re-engineering is required. The cost of training healthcare providers to effectively employ AI is another concern with AI [161]. One major obstacle to the effective use of AI in healthcare is the lack of sufficient experimental data to confirm the effectiveness of AI-based medications in planned clinical trials. AI research has primarily taken place in settings that do not involve actual patients. Translation of results to a broader context may thus prove challenging. Similarly, due to a lack of empirical data and rutted research quality, institutions are hesitant to implement AI-based solutions [167]. As a whole, AI has a lot of drawbacks, such as the high expense of developing AI-based apps, the fact that it makes people lazy, the fact that it makes people unemployed because AI can do mundane jobs, and the fact that robots can't feel emotions or be creative [168].

CONCLUSIONS

There are several healthcare applications that are utilizing AI technologies. Medical imaging and diagnostic services, the fight against the pandemic, virtual patient care, increased patient engagement and treatment plan adherence, reduced administrative burden for healthcare professionals, innovation in drugs and vaccines, exercise compliance monitoring, gait analysis for technology-assisted rehabilitation, and other uses for these technologies have all been developed. While AI is making great strides in healthcare, it is not without its fair share of technological, ethical, and governmental hurdles. It uses sensitive and confidential data that is bound by legal panels, which creates concerns about data security and privacy. The lack of empathy and other human traits in AI, as well as the accuracy of current health data, could impede its usefulness in solving problems. While AI does a better job when it's working effectively, it still can't take the place of the personal relationships that make up teams. Since computers are unable to develop emotional bonds with people, they are unable to carry out human tasks like teamwork and team management. As we move forward with AI governance, one of the most pressing issues will be ensuring that the technology is built and used in a manner that respects human interests while also considering technological, ethical, and societal considerations. This study contributes to the current body of knowledge on the use of artificial intelligence (AI) in healthcare administration, including virtual patient care, virtual medical research and drug discovery, patient engagement and adherence, rehabilitation, and medical imaging and diagnostics. Furthermore, this represents the most recent revision to the literature that deals with the technological, social, ethical, and governance issues that healthcare providers encounter while implementing AI.

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