Egyptian Journal of Chemistry
http://ejchem.journals.ekb.eg/

Artificial Intelligence for Improved Health Management: Application, Uses, Opportunities, and Challenges-A Systematic Review

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Abstract

Aims: This study aims to provide a comprehensive overview of the role of artificial intelligence (AI) and machine learning (ML) in various domains, particularly healthcare, and its implications for international development and public health. It seeks to explore the applications, challenges, and future directions of AI and ML technologies in shaping healthcare delivery, disease prediction, diagnosis, treatment planning, and public health interventions. **Methods:** The study employs a systematic review approach to synthesize the literature on AI and ML applications in healthcare, drawing insights from a wide range of sources including research articles, reports, and news articles. Various aspects of AI, such as deep learning, natural language processing, robotics, and predictive modeling, are examined to understand their potential in addressing healthcare challenges and improving health outcomes. **Results:** The review identifies many AI applications in healthcare, ranging from medical imaging and diagnostics to personalized medicine and predictive analytics. These technologies have demonstrated promising results in enhancing clinical decision-making, optimizing healthcare delivery, and facilitating early disease detection. However, challenges related to data privacy, algorithm bias, regulatory compliance, and ethical considerations remain significant barriers to widespread adoption. **Conclusion:** AI and ML hold immense potential to revolutionize healthcare delivery and public health initiatives, offering opportunities for enhanced efficiency, accuracy, and accessibility of healthcare services. Nevertheless, careful consideration of ethical, legal, and social implications is crucial to ensure responsible and equitable deployment of these technologies. Collaborative efforts among policymakers, healthcare providers, technologists, and other stakeholders are essential to harness the full benefits of AI while addressing its challenges.

Keywords: Artificial intelligence, Machine learning, Healthcare, Public health, international development, Ethical considerations, Predictive analytics, Deep learning, medical imaging, Personalized medicine.

1. Introduction

The healthcare industry is rapidly embracing and progressing swiftly with artificial intelligence (AI) due to its ability to leverage big data and extract valuable insights that support evidence-based clinical choices and enable value-based treatment. Healthcare executives need to understand the state of AI technologies and how they may improve the effectiveness, security, and usability of healthcare services, which will help drive the industry's digital transformation. Artificial Intelligence is having a growing impact on almost every aspect of healthcare, from medication research in real-world settings to clinical decision support at the point of care. However, there are several obstacles and costs associated with the development and application of AI technology. For health companies to successfully integrate AI, several challenges must be overcome. The challenges encompass the following: (1) inadequate comprehension of the potential benefits and constraints of particular AI technologies; (2) unclear approaches for integrating diverse AI technologies into current healthcare systems to tackle the most pressing problems encountered by healthcare institutions; (3) a shortage of skilled personnel for AI deployment; (4) incompatibility of AI technologies with antiquated infrastructure; and (5) restricted availability of high-quality and varied medical data required for training Machine Learning (ML) algorithms [1, 2]. Similar challenges arise in other fields, such as nanotechnology research. The integration of artificial intelligence (AI) into

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Receive Date: 09 September 2024, Revise Date: 02 October 2024, Accept Date: 03 October 2024
DOI: 10.21608/ejchem.2024.319621.10386

nanotechnology research presents significant challenges. A recent review [1-5] highlights several key obstacles, including the need for robust datasets, the development of specialized AI algorithms, and the ethical considerations surrounding the use of AI in this field.

In many high-income situations and high-income countries, AI is changing the way health services are delivered, especially in specialty areas like pathology and radiology [3-5]. The increased accessibility of large-scale datasets and cutting-edge analytical techniques that make use of these datasets have made this advancement possible. Concurrently, improvements in mobile computing power and information technology (IT) infrastructure have raised hopes that AI could also help address health issues in low- and middle-income countries (LMICs) [6]. The world's attempts to meet the sustainable development goals (SDGs) about health are hampered by issues including the severe scarcity of health workers and inadequate public health surveillance systems [7-8]. These challenges are not unique to these countries, but they are particularly important because of how they affect rates of illness and mortality [9-10]. AI-driven health devices may resolve a lot of these and other systemic problems. For example, in certain situations, AI-driven interventions have aided in clinical decision-making, which has lessened the workload for medical professionals [11]. In addition, recent advances in AI have made it possible to detect illness outbreaks earlier than with conventional methods, which has improved the timeliness of policymaking and program planning [12]. Even though these treatments seem promising, there are several moral, legal, and practical issues that must be resolved before they can be widely implemented or scaled up in LMICs. A growing number of major donor agencies and the global health community have recognized how urgent it is to address these problems to guarantee that populations in low- and middle-income countries (LMICs) benefit from advances in AI and digital health [13]. Numerous international gatherings have occurred since 2015 [14-16]. For instance, the World Health Assembly adopted a resolution on digital technology for health coverage for all people in May 2018 [17]. "By 2030, every adult should have affordable access to digital networks, as well as digitally-enabled financial and health services, as a means to make a substantial contribution to achieving the SDGs," the United Nations Secretary General's High-Level Panel on Digital Cooperation recommended in 2019 [18].

Additionally, because AI has the potential to bring about revolutionary advances in the treatment of human diseases and public health, it has attracted a great deal of interest from researchers, doctors, technology and program developers, and consumers across a variety of areas [19-22]. By 2021, hospitals are expected to invest $6.6 billion yearly in AI-related technology, according to Accenture [23]. "AI applications could create up to $150 billion in annual savings for U.S. healthcare by 2026," according to Safavi and Kalis [21]. AI-supported technologies are essential for improving physicians' decision-making processes for diagnoses and treatments since they can learn from enormous amounts of medical research and patient treatment data [24-26]. "AI-based diagnostic algorithms are applied in the detection of breast cancer, serving as a ‘second opinion' to assist radiologists in image interpretations," according to Shiraishi et al. [27]. 3D tumor spheroid models are increasingly being used in cancer research to better understand tumor growth and response to treatments. Advancements in microfluidic technology, such as the use of surface acoustic streaming to generate these models rapidly [27,28], are providing valuable insights for drug discovery and personalized medicine especially if used with the aid of AI. Additionally, it has been discovered that AI technology can identify skin cancer more accurately than licensed dermatologists [28]. Due to their analysis based on a wealth of information and data, these diagnoses are handled more rapidly and effectively [29]. Furthermore, sophisticated virtual human avatars are being used to carry out the essential dialogues required for the diagnosis and treatment of patients suffering from mental disorders [30].

Miyashita and Brady [31] provided an example of a group of hospitals serving 500,000 people in southeast England that released patients equipped with Wi-Fi-enabled armbands to remotely monitor vital signs, such as respiratory rate, oxygen levels, pulse, blood pressure, and body temperature. In this instance, the use of AI programs that analyze patient data in real time resulted in a considerable reduction in hospital readmission rates and ER visits. The need for costly house calls also dropped by twenty-two percent. Over time, the industry average of 50% was surpassed by 96% adherence to treatment plans. Similarly, Grady Hospital, a public hospital in Atlanta, USA, announced savings of $4 million after implementing an AI-enabled tool to identify patients who are “at-risk,” which resulted in a 31% decrease in readmission rates over a two-year period [31].

In the present era and under the conditions of COVID-19, the importance of AI was explored in more detail. A wide range of techniques are included in artificial intelligence (AI), such as machine learning, computer vision, and natural language processing [32]. Large-scale data analysis, prediction, and pattern recognition can all benefit from these methods. AI has been used to identify novel pharmaceutical targets, predict the course of infectious diseases, and diagnose illnesses, and it has the potential to completely transform the healthcare industry [33]. Additionally, AI has been used to support drug administration and discovery as well as the interpretation of medical imaging [34]. However, AI's focus moved from medicine to public health during the COVID-19 epidemic. Artificial Intelligence (AI) was crucial in predicting the COVID-19 pandemic, expediting contact tracking, guaranteeing pharmacovigilance, and enabling prompt testing and identification [35-36]. The implementation of these epidemiological informatics tools aided international initiatives aimed at reducing the COVID-19 virus's transmission and improving patient care.

The technique of identifying and averting system malfunctions while projecting the dependability and residual usable life (RUL) of its constituent parts is known as health management [37]. System health management research has increased dramatically over the past few decades to address a variety of failures, ranging from component level to system level [38] and Lee et al. [39]. Numerous techniques still need sophisticated triggering systems that can gather enough information about the failing component, the type of problem, and how it affects the overall performance of the system, even after in-depth research on these ideas [40-41]. As a result, efforts are concentrated on integrating technologies for prognostic, diagnostic, and anomaly detection throughout systems and related platforms. This capacity to foresee and isolate approaching malfunctions might uncover persistent problems to reduce risks while assisting in the economical maintenance of system performance. An additional consequence is the heightened focus on data collecting as an essential component of contemporary engineering systems. Data-driven methods provide a new bottom-up paradigm for controlling system failures and forecasts, in contrast to conventional top-down approaches. This change has made data analytics in diagnostic technology a top research goal.

The healthcare sector is rapidly integrating artificial intelligence (AI) to leverage big data for evidence-based clinical decisions and value-based treatment. AI is revolutionizing various aspects of healthcare, from drug research to clinical decision support, but faces significant challenges and costs. Healthcare executives must understand AI technologies to improve service effectiveness, safety, and accessibility. Despite extensive research, AI integration requires overcoming challenges such as understanding AI capabilities, developing clear integration strategies, addressing workforce shortages, ensuring compatibility with existing infrastructure, and accessing diverse medical data for machine learning. AI has significantly impacted high-income countries, particularly in specialties like radiology and pathology, and offers potential solutions for health issues in low- and middle-income countries (LMICs). AI has proven crucial during the COVID-19 pandemic for forecasting, contact tracing, and rapid detection, highlighting its importance in public health. Global efforts and investments in AI are essential for achieving sustainable development goals and improving healthcare outcomes worldwide.

History of AI and Deep Learning in Healthcare Management:

The goal of the 1960s artificial intelligence (AI) research was to build systems (**Figure 1**) that could mimic human intelligence [42]. Expert systems, which employed information from human specialists to give decision assistance for medical diagnosis and treatment planning, were the main focus of early AI applications in the healthcare industry. Expert systems continued to be a major focus of AI research in healthcare during the 1980s and 1990s, but interest in machine learning and natural language processing also started to grow [43]. Researchers have been able to explore the possibilities of artificial intelligence (AI) in medical diagnosis, drug discovery, and public health surveillance because of the accessibility of vast medical databases and sophisticated computer systems. Significant developments in machine learning, natural language processing, and computer vision during the 2000s made it possible to create increasingly complex artificial intelligence (AI) systems that could analyze massive datasets and forecast future events [44]. As a result, AI-based diagnostic tools were developed, including ones that use medical picture analysis to find cancer and other disorders. Large volumes of unstructured data, including electronic health records, could be analyzed thanks to advancements in text mining and natural language processing techniques, which produced insightful results.

Interest in the use of AI in public health, particularly in surveillance and predictive modeling, has grown recently. Public health experts have been able to take preventive action by using AI algorithms to forecast the spread of infectious diseases like influenza or COVID-19 [45]. AI has also been used to track the transmission of disease and identify possible outbreaks by analyzing massive datasets from social media and other sources. The rising availability of large data sets and sophisticated computational resources has led to an expansion of the use of AI in public health to encompass tailored treatment plans and drug development [46]. In general, the use of AI in public health has progressed from simple expert systems to sophisticated systems that can evaluate and forecast vast amounts of data. Healthcare AI poses ethical and legal concerns about data privacy, safety, transparency, fairness, algorithmic biases, and the philosophical implications of AI on human judgment, even while it offers many potential benefits for public health [47-49]. To successfully incorporate AI technology into healthcare systems, several issues need to be resolved.

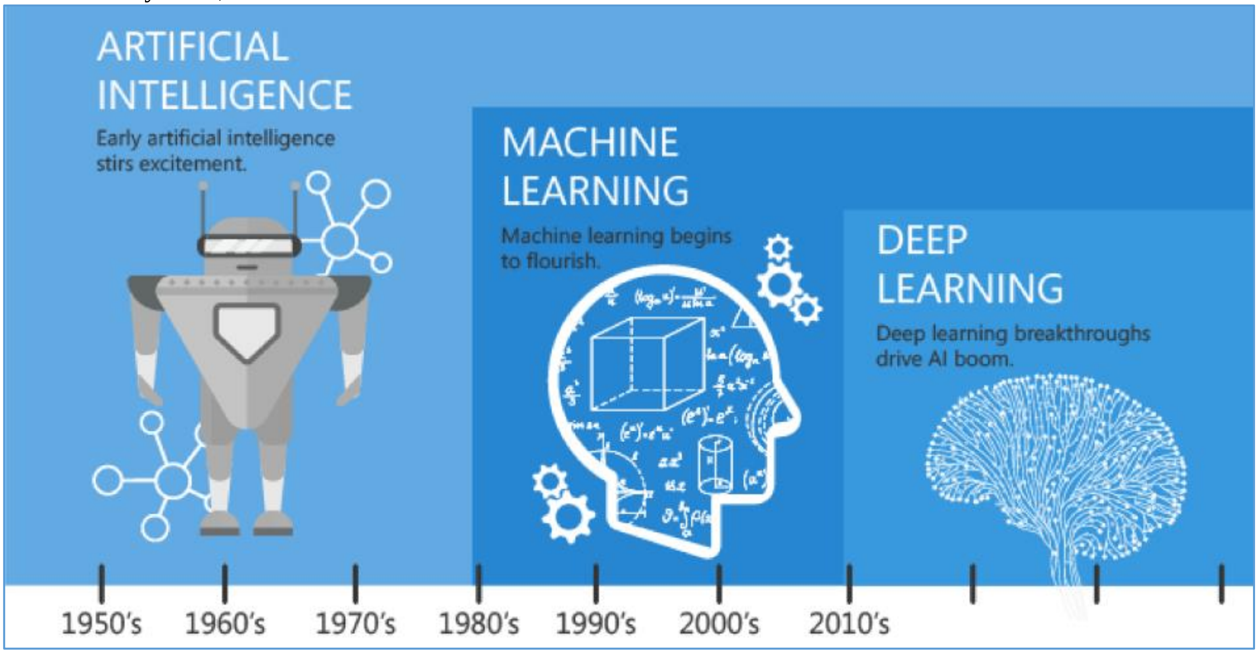

Figure-1: History of AI Revolution [50].

AI, Deep Learning, and Machine Learning: Current Status

In practical terms, artificial intelligence refers to computer programs that mimic or exhibit specific traits of human intelligence or intelligent behavior, such as reasoning, learning, and problem-solving [51]. AI, then, is the umbrella term for a wide range of intelligent behaviors and processes produced by computer models and algorithms. Recent developments in computational models and algorithms, along with potent computers and abundant data availability, have accelerated the advancement of artificial intelligence (AI), particularly in the fields of robotics, machine learning (ML), natural language processing (NLP), AI voice technologies, and AI assistants. These advancements have produced fresh, potent approaches to challenging real-world issues in big data analytics, speech recognition, image recognition, and healthcare.

Artificial intelligence (AI) is dominated by machine learning (ML), which has led to several recent developments in the field. In essence, machine learning (ML) uses algorithms to identify patterns in input data to train predictive models. These models are then used to produce predictions from newly uncovered data. One of the key components of AI is that machine learning algorithms are capable of learning from experience and improving on their own. ML is widely used in a variety of AI technologies, including robotics, speech technology, and natural language processing (NLP). It provides the framework for comprehending the promise and constraints of AI technologies. Reinforcement learning (RL), deep learning, supervised learning, and unsupervised learning are important machine learning algorithms. Supervised learning, which is frequently used in healthcare for clinical decision support and predictive analytics, involves using labeled data to find patterns that correlate outcomes with input. Unsupervised learning, on the other hand, is helpful for jobs like disease risk prediction and individualized treatments since it finds data structures and patterns purely from input. Reinforcement learning enables self-directed learning through interactions with the surroundings, making it appropriate for activities requiring sequential decision-making, such as robotically assisted surgery. Operating across numerous levels of abstraction, deep learning has led to advances in a number of fields that depend on big datasets and feature recognition. While machine learning (ML) has shown remarkable performance in complicated tasks involving large amounts of data, it could not be sufficient for tasks requiring domain-specific expertise or common sense reasoning, which would make it difficult to comprehend results and fix recognized flaws [52].

Natural language processing (NLP) is the automatic analysis and interpretation of human languages, mostly textual, using computational methods. The integration of machine learning (ML) techniques with natural language processing (NLP) has resulted in notable progress in several domains, including speech recognition, text classification, machine translation, question answering, sentiment analysis, information extraction, and search engines. There is an enormous amount of unstructured textual data in the healthcare industry, including prescription orders, test results, lab reports, doctors' notes, and discharge instructions. From this abundance of descriptive data, NLP techniques can extract important information that improves diagnosis and therapy suggestions. Healthcare practitioners can make timely and educated judgments by utilizing machine learning and natural language processing (ML and NLP) to quickly process large volumes of textual and imaging data. This has the potential to revolutionize patient care and health service delivery [53].

For humans, voice communication comes naturally and intuitively. Artificial intelligence (AI) voice technology is transforming human-machine interaction by making it easier to obtain, understand, use, and store health information. Voice interfaces can improve user experiences by resolving issues with complicated system operations and text-based information sharing. Voice technology is becoming widely used in a variety of industries, and efforts are being made to integrate it into healthcare to overcome information-related challenges that patients and healthcare workers face. Voice technology is being used by many EHR manufacturers and healthcare providers to expedite clinical recording processes because of the complexity of today's EHR systems. Consumer-facing AI assistants like Google Assistant, Cortana, Alexa, and Siri are now able to handle certain repetitive medical chores like appointment scheduling and prescription reminders. But when it comes to answering health-related questions, existing AI voice assistants are not as trustworthy as text-based chatbots like Babylon, Ada, and Buoy—which have experienced more commercial success. Even while text-based chatbots frequently limit user input to preset words and phrases, which discourages user initiative in conversation, investors and major tech corporations as well as startups have great hopes for the development of more sophisticated AI voice health assistants. Future developments are anticipated to provide unrestricted language input and natural dialogues akin to those in humans, which should improve accessibility and communication in the healthcare industry [54-55].

Medical robots are a prime example of what the aforementioned AI technologies are capable of. They support several healthcare activities, such as supported living, social contact, surgery, and rehabilitation. AI-assisted surgical robots, which use preoperative medical records to guide surgical instruments in real-time during treatments, are among the commonly used medical robots. These locally and remotely operated robots are frequently used in orthopedic, laparoscopic, and neurologic operations. Robot-assisted surgery is less intrusive than traditional surgery, which means fewer difficulties, blunders, and hospital stays. Additionally, robots help with geriatric care, assist with stroke victims' rehabilitation, and make it easier for medical supplies and equipment to be delivered. In the not-too-distant future, robots might be able to keep an eye on patients' vital signs and act on their own when necessary [56].

Applications of AI in Healthcare Management:
Predictive Modeling:

To predict the spread of infectious diseases like COVID-19 and influenza, public health uses predictive modeling, which combines statistical models and machine learning approaches. Predictive models find patterns and trends in data from previous epidemics combined with variables like population demographics and weather patterns, which help guide public health measures. Predictive modeling is a key use of AI in public health because of its capacity to enhance the forecasting of disease transmission and direct public health actions. The application of artificial intelligence (AI) to predictive modeling seeks to improve the precision, efficacy, and practical insights in public health decision-making, specifically in disease forecasting, risk assessment, and spatial modeling. Because of the difficulties that traditional approaches in these fields frequently have with data complexity, pattern recognition, and prediction accuracy, artificial intelligence (AI) has emerged as a game-changing way to overcome these obstacles and provide more fruitful results. However, there are barriers to well-informed decision-making, efficiency, accessibility, and collaborative research in public health due to the unclear classification and summarization of traditional and AI-based predictive modeling techniques, such as disease forecasting, risk prediction, and spatial modeling (**Figure 2**). The lack of structured classification makes choosing a method more difficult, causes the implementation to take longer and prevents wider adoption. To improve the area, it is imperative to provide a uniform taxonomy and concise summaries for each strategy. This will help practitioners navigate methodologies effectively, accelerate decision-making processes, and promote collaboration in research [57-62].

One important use of AI in public health is disease forecasting, which has the potential to improve our capacity to anticipate the spread of infectious diseases and, as a result, educate and guide public health initiatives. In the past, time-series analysis and traditional statistical methods were used to forecast illnesses. But with the development of AI, more sophisticated algorithms are now able to be used, utilizing a variety of data sources to produce accurate more accurate predictions. In particular, machine learning algorithms have become a major trend in artificial intelligence (AI) for illness prediction. These algorithms may analyze several data streams, such as social media and electronic health records, to find trends and anticipate the spread of diseases [64-67].

In addition, the availability of large data sets and sophisticated computing power has increased, making it possible to analyze a wide range of complex data sources, including social media, sensor data, and electronic health records. This makes it easier to predict future trends and patterns, which were previously difficult to identify, with greater accuracy. AI has the potential to be useful for disease forecasting in public health by analyzing vast amounts of data, seeing patterns and trends, and projecting future results. This information may then be used to inform public health actions and slow the spread of infectious illnesses. Nevertheless, there are still issues to be resolved, such as the fact that the accuracy of predictions depends on the completeness and quality of training data, as well as the moral and legal implications of data security and privacy when using AI in public health [68-70].

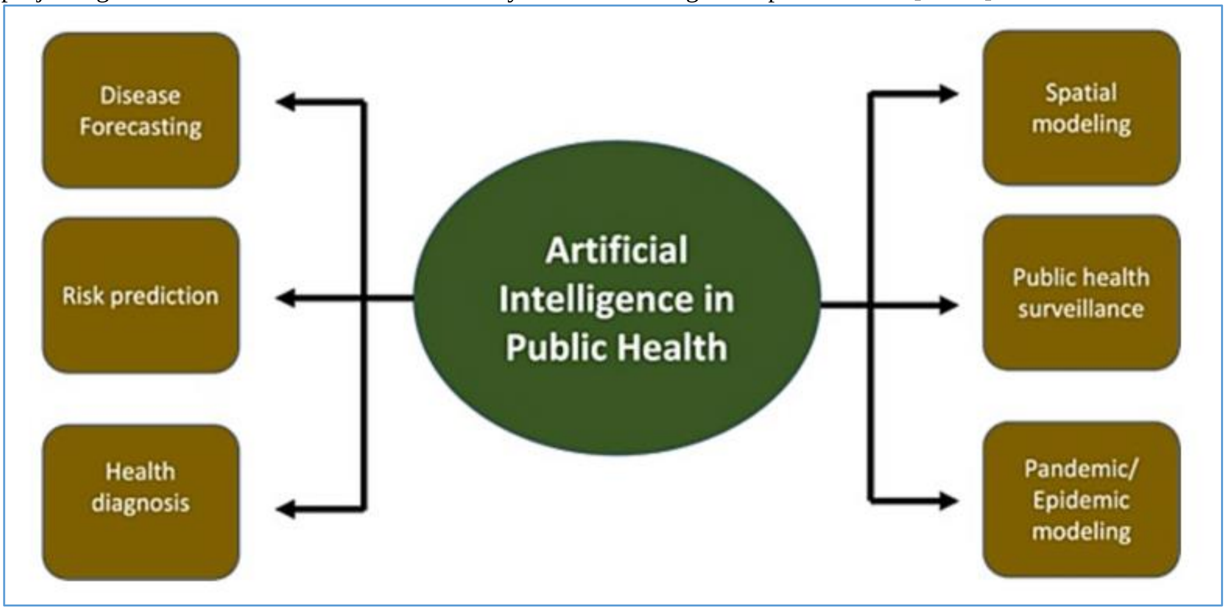

Figure 2: AI predictive Modeling [63].

In the future, real-time data from the integration of AI with other technologies, such wearables and the Internet of Things (IoT), could improve the predictability and accuracy of forecasts. By clarifying the underlying mechanics of predictions, explainable AI (XAI) solutions are also being developed to improve the accountability and transparency of AI-based illness forecasting systems. Another area with room to grow is personalized disease forecasting, which uses algorithms to examine data from electronic health records and other sources to anticipate a patient's likelihood of developing a particular disease and to inform treatment choices. Additionally, by combining geographic data with Geographic Information System (GIS) technology, disease forecasting can benefit from focused interventions that improve local-level predictions [71]. To sum up, predicting the future spread and effect of illnesses with accuracy is the primary problem in disease forecasting. This problem is solved by AI, especially machine learning and deep learning algorithms, which analyze massive datasets quickly, find connections that aren't obvious, and spot complex patterns. Providing early alerts, practical insights, and mitigation techniques for disease epidemics is the aim. AI is being used in disease forecasting, and examples like Google AI's model for predicting COVID-19 cases show how useful it can be in informing public health decisions and enhancing patient outcomes [72-73].

Because it permits focused illness treatment and preventative efforts, risk prediction is crucial to public health. Conventional risk prediction techniques can be laborious and unreliable at times because they entail manual calculations based on clinical and demographic data. However, by evaluating massive datasets, like electronic health records, and applying machine learning algorithms to find patterns and gauge the likelihood of diseases, artificial intelligence (AI) has the potential to improve the efficacy and precision of risk forecasts. To further improve risk assessments, these algorithms can also examine complicated data sources like genetics and medical pictures. AI risk prediction in public health is expected to grow in the future, especially when it is combined with other technologies like genomics and wearables, which can supply more accurate and timely data for prediction. Additionally, by clarifying the algorithmic decision-making process, explainable AI (XAI) technologies can increase the accountability and transparency of AI-based systems, hence promoting trust in AI applications in the healthcare industry. The main difficulty in risk prediction is determining which people are more likely to get a given disease than others. Conventional methods might not be able to adequately capture nuances in risk variables or changing circumstances. This problem is solved by

AI techniques like machine learning and natural language processing, which integrate many data sources, find non-linear relationships, and reveal latent patterns. Customized interventions, efficient resource allocation, and enhanced individualized healthcare methods are the objectives. Heart attacks, strokes, and auto accidents are only a few examples of the events that AI applications in risk prediction cover. For example, IBM Watson Health has created a model that can 90% accurately forecast the risk of a heart attack [74-76].

A key component of public health is spatial modeling, which is the process of examining geographic data to find patterns and trends in health outcomes. This is because it makes it easier to focus interventions at regions with the highest rates of illness. Conventional spatial modeling techniques, such manual data gathering and analysis, can be laborious and prone to errors. But using AI can improve spatial modeling's precision and effectiveness, which will ultimately lead to better public health results. Large-scale geographic data, including satellite photos, can be analyzed by machine learning algorithms to identify patterns and forecast the spread of illnesses. These methods have been applied, for instance, to predict the risk of diseases such as dengue fever, considering variables like dengue cases, transmission rates, and mosquito biting rates. An important development in spatial modeling is the combination of artificial intelligence (AI) and geographic information systems (GIS). This combination enables the study of various datasets, including social media and electronic health records, in a geographical context. More precise forecasting and the discovery of hitherto unidentified patterns are made possible by this integration [77-80].

The use of deep learning algorithms, which can scan complex data, including genetics and medical pictures, to detect patterns indicative of illness risk in certain places, is another rising trend in AI-driven spatial modeling. For example, deep learning has been used by researchers to look at the connection between certain brain regions and neurological conditions. Additionally, by examining audio recordings of patients' coughs in addition to symptom reports, AI has been used to improve the diagnosis of respiratory illnesses. In response to COVID-19, Gunasekeran et al. carried out a thorough scoping review that highlighted the use of AI in predictive modeling and concentrated on digital health applications. In order to predict the spread of illness, identify high-risk populations, and guide targeted therapies, artificial intelligence (AI) algorithms may evaluate large datasets, including demographic data, health records, and environmental factors. The main difficulty in spatial modeling is to identify geographic trends and patterns in health outcomes. At the local level, traditional approaches frequently fail to produce reliable forecasts due to the complexity of spatial data. These issues are addressed by AI in conjunction with GIS by using machine learning and deep learning techniques to recognize complex spatial patterns, including disease clusters, and to facilitate data-driven decision-making for focused interventions. For instance, a model that can forecast the spread of wildfires was created at the University of California, Berkeley [81-84].

AI and Medical Records:

The abundance of data included in electronic health records (EHRs), which are digital records of a patient's health information including medical history, medications, lab results, and other pertinent information, is extremely beneficial to public health research and practice. Although electronic health records (EHRs) are widely used in healthcare settings, the volume of data they contain can make manual analysis difficult, requiring the creation of new tools to extract insights. Artificial intelligence (AI) has developed as a method to increase the accuracy and efficiency of EHR data processing, ultimately enhancing public health outcomes. The analysis of EHR data depends heavily on machine learning algorithms, which make it possible to spot patterns and make predictions about the spread of disease. By obtaining data from unstructured text sources, including doctor's notes, natural language processing (NLP) techniques improve electronic health record (EHR) analysis even more by providing a deeper understanding of patients' health conditions. More and more deep learning algorithms are being used to estimate patient outcomes, such as readmissions to hospitals, and to guide public health policy decisions.

There are obstacles when using AI for EHR analysis, notwithstanding the possible advantages. Prediction accuracy is dependent on the completeness and quality of the data used to train algorithms, underscoring the significance of obtaining high-quality data while maintaining patient privacy and adhering to legal requirements such as HIPAA. Additionally, developing trustworthy AI algorithms is difficult due to the diversity of data included in EHRs, which includes time series and unstructured language. Though algorithms can predict disease risk and direct treatment decisions for individual patients, the future of artificial intelligence (AI) for electronic health records (EHRs) appears promising, especially in the field of personalized medicine. The goal of this field's growing research is to use NLP and AI to extract insights from unstructured textual data stored in electronic health records. By combining structured EHR data with text that has been processed using natural language processing (NLP), techniques like Named Entity Recognition (NER) and sentiment analysis work in tandem with AI techniques like machine learning and deep learning to enable personalized medicine. Recurrent neural networks (RNNs) and transformer-based architectures (BERT) are two examples of deep learning models that are particularly good at identifying contextual linkages in EHR narratives. This allows for precise information extraction and semantic interpretation of medical literature for analysis that is relevant [85-90].

Real Applications of AI in Healthcare Management:

According to the World Health Organization (WHO), lifestyle factors, including exercise, diet, sleep, stress reduction, substance and medication use, and recreation, account for 60% of individual health and quality of life [91-92]. With the advancement of AI-aided technologies, lifestyle interventions and reminders based on an individual's vital signs can now be provided throughout the day via digital devices. These AI-based technologies are poised to transform healthcare systems within organizations, optimizing operations, patient interactions, and care services to improve overall efficiency and patient outcomes. In terms of diagnostic assistance, AI is expected to play a crucial role in facilitating the diagnosis of specific diseases, particularly given that diagnostic errors contribute to a significant portion of medical errors and associated deaths [93]. Several healthcare organizations have already leveraged AI for diagnostic purposes with promising results [94]. For instance, the Mayo Clinic implemented an AI-based solution for cervical cancer screening, demonstrating higher accuracy rates compared to human experts [95-96]. Similarly, the Moorfields Eye Hospital in London introduced an AI solution for identifying eye disease signs with high accuracy, matching the performance of world-leading experts [97]. In South Korea, medical centers have evaluated AI-assisted diagnostic systems, showing varying levels of consensus between medical staff and AI recommendations, particularly in the context of cancer treatment decisions [98]. In China, the Guangzhou Women and Children's Medical Center utilized AI-based technologies to evaluate and diagnose pediatric diseases, achieving high accuracy rates comparable to experienced physicians [22]. However, it is noted that while AI may assist junior physicians in diagnoses, it may not necessarily outperform experienced physicians [22]. The introduction of AI for oncology at the Manifal Hospital in India revealed differences in diagnoses between medical staff and AI judgments, highlighting variations depending on the type of cancer [99]. Overall, the integration of AI into healthcare systems, as demonstrated by IBM Watson Health, aims to support informed decision-making based on scientific evidence and improve patient satisfaction by providing comprehensive treatment options [99].

In response to the significant paperwork burden often faced by healthcare staff, the industry is increasingly transitioning to electronic systems that digitize and integrate medical records, facilitated by AI-based technology. Moreover, chatbots are recognized as potentially effective tools for engaging in conversations with patients and family members within hospital settings [100]. Real-world applications of AI-based technologies in healthcare systems include the use of Microsoft's AI digital assistant Cortana at the Cleveland Clinic, where it aids in identifying potential at-risk patients under ICU care through predictive and advanced analytics. Similarly, the University of Pittsburgh Medical Center employs an AI-assisted system that learns from conversations between doctors and patients in hospital rooms [101].

Johns Hopkins University Hospital collaborates with GE Healthcare partners to utilize predictive analytics based on AI technologies, resulting in improved operational efficiency. Their Command Center integrates data from multiple IT systems, leading to faster bed assignments, reduced transfer delays, and improved patient acceptance rates [101]. In addition to administrative workflow assistance, AI is applied in clinical settings, such as robotic-assisted surgery, which offers surgeons high precision, controllability, and flexibility. Cedars-Sinai Hospital employs Amazon's Alexa robots as virtual nursing assistants, assisting patients with daily routines, medication reminders, and answering medical questions [94]. At Eunpyeong St. Mary's Hospital of the Catholic University of Korea, the AI robot Paul aids medical staff during patient visits by transcribing electronic medical records in real-time, providing patient information, and guiding patients throughout the hospital. Another robot, Maria, serves as a guide in the hospital lobby, providing directions and appointment schedules to patients [102]. These examples illustrate the diverse applications of AI in healthcare, ranging from diagnostics to administrative tasks, ultimately enhancing efficiency and patient care. However, to ensure the continuous expansion and improvement of AI-supported systems, it is essential to address various issues within the healthcare industry.

AI Opportunities:

The market must create customized systems for each medical specialty that include machine learning algorithms trained on a significant number of instances that include patient data from a variety of ethnic and cultural backgrounds in order to improve the accuracy of AI-applied diagnostic systems [103]. As additional instances are added by researchers and healthcare experts, these AI systems can develop and get better, making them more capable of diagnosing patients. Artificial intelligence (AI) in medicine offers both dystopian and utopian viewpoints. From an idealistic perspective, it presents a wealth of chances to advance illness management, raise the standard of care and patient satisfaction, encourage patient participation in the course of treatment, reduce medical errors and healthcare expenses, and maximize the effectiveness of healthcare professionals [104-105]. On the other hand, the dystopian perspective poses important problems. Cybersecurity concerns increase with increased use of patient data for analytics, putting privacy and security at risk [106]. Additionally, there's a chance that automation may result in job displacement and complicate the accountability for medical errors [107]. The ethical and astute application of AI-based technologies in healthcare requires addressing both the positive and negative elements of these technologies. Stakeholders can guarantee the responsible and widespread use of AI in the healthcare sector by closely examining these problems.

A major turning point in the use of data-driven methodologies to transform medical research was the introduction of IBM Watson, which sparked a general interest in utilizing cutting-edge digital technology to promote public health and raise the standard of patient care [108]. Empirical instances highlight the critical function that cutting-edge technologies play in enhancing medical personnel in a variety of patient treatment domains. To treat ailments like high blood pressure and lung illness, for example, AI-supported algorithms, such MRI-based cardiac motion algorithms, provide more precise data [109]. AI has the potential to improve patient care services, especially in impoverished rural populations, as evidenced by the efficacy of AI-driven diagnostic algorithms in diagnosing rare genetic illnesses [110]. Artificial Intelligence has demonstrated exceptional efficacy in handling substantial amounts of radiology data, contributing to improved care services, namely in the field of medical imaging [111]. AI-enabled software increases efficiency by reducing manual labor and streamlining procedures for medical personnel, all while improving diagnostic accuracy [111]. Furthermore, AI systems are always learning from study and data, honing their diagnostic precision to the point where it is on par with or better than that of medical professionals, reducing errors and enhancing the skills of medical personnel [111].

In order to accurately diagnose diseases and ensure patient safety, as well as to improve treatment outcomes and the quality of care received, patient engagement and participation are essential. By enabling people to take charge of their health and follow treatment programs, technologies like smartphone-based health coaching applications promote healthier habits and lower the risk of chronic diseases. This increases patient involvement [112-113]. Patients' involvement in treatment procedures can be further improved by educating them about the advantages of AI-based medical systems. This will increase the variety of treatment alternatives available and improve patient outcomes overall. In a number of medical sectors, AI-supported systems have been effective in lowering medical errors and improving service quality [114]. Artificial intelligence (AI) technologies facilitate the detection and treatment of diseases, lower error rates, and increase operational efficiency by supporting medical personnel in tasks like colonoscopy examinations [114]. Moreover, AI's contribution to operational advancements like nursing robots and chatbots simplifies repetitive operational tasks and boosts overall productivity [114].

Despite ongoing worries about AI taking jobs away, historical trends indicate that technical developments have increased productivity and created new job opportunities [115]. For example, AI-enabled health coaching applications have improved treatment outcomes and fostered long-lasting relationships with clients by creating new jobs in personalized coaching and support services [116]. Additionally, by lowering mistake rates, shortening the time needed for diagnosis and treatment, and looking into new opportunities to extend care services, AI-based systems improve productivity [115]. Widespread use of AI in healthcare has the potential to lower overall costs while raising the standard of care [116]. Effective AI uses in illness prevention, diagnosis, and treatment can result in significant financial savings that are advantageous to both individual patients and society at large [116]. Economies can be redirected to fund illness prevention programs, which will improve the standard of living for all citizens and advance public health and wellbeing in general.

Challenges of AI in Healthcare Mangement:

There are potential and problems associated with integrating AI technologies across multiple industries, especially in the healthcare industry where human lives are at risk. The employment of AI systems raises important questions about accountability, particularly when mistakes or unfavorable outcomes occur. There are many intricate managerial, ethical, and technical considerations when deciding who is responsible—the medical staff, the hospital, or the system design firm [117]. Furthermore, studies on the ethical implications of AI technology have not kept up with their rapid growth, making the creation of regulatory frameworks to guarantee responsible AI use necessary [117]. The creation and application of AI systems must be guided by ethical behavior patterns in order to conform to society norms and values, especially in the healthcare industry where unfavorable outcomes might have significant effects [117].

A further obstacle is the possible expansion of the "AI divide," especially in the healthcare industry, where patient confidence in medical personnel is crucial [118]. The adoption of AI-based systems can put this trust in jeopardy since patients, particularly those who are not familiar with digital technology, might find it difficult to have faith in artificial systems [117]. In order to close this trust gap, medical personnel and patients must effectively communicate while reassuring people of the advantages of artificial intelligence (AI) in improving care delivery and results. In the age of AI, cybersecurity issues are also quite important, especially when it comes to data security and privacy [119]. Because AI systems rely on large datasets, data collecting and sharing privacy concerns are brought up. To reduce barriers to AI research, confidentiality laws and regulations must be followed [120]. To protect individual rights and social values, AI technology decision-making procedures also need to take ethical, legal, and moral factors into account.

Traditional ideas of managerial control and healthcare delivery methods are also under threat from the introduction of AI in the field [116]. The healthcare industry is moving toward more integrated, patient-centric care models as a result of AI's capacity to transcend time and place [116]. In order to enhance patient outcomes, this transformation requires a shift away from traditional bureaucratic governance structures and toward dynamic, networked care delivery systems that make use of AI technologies and interdisciplinary skills. Additional important factors to consider are worries about AI replacing jobs and the necessity of worker education and training [121]. AI may make some employment obsolete, but it also opens up new career prospects for competent workers in support, development, and implementation roles [121]. Professionals need to be equipped with the skills necessary to navigate the AI-driven healthcare landscape. Companies like Amazon and educational institutions like medical schools have launched effective workforce training programs that do just that [121]. Additionally, the potential for AI to strengthen patient-provider relationships highlights the significance of integrating AI-related technology and teaching into medical school curricula [121].

To ensure the appropriate and fair implementation of AI in public health, governments and stakeholders must prioritize data security, privacy protection, and ethical concerns while tackling these difficulties [122-123]. Cooperation projects, like data sharing programs and federated learning, are viable ways to protect patient privacy while optimizing the advantages of AI-driven insights [124-128]. The healthcare sector may leverage artificial intelligence (AI) to enhance patient outcomes and promote public health by following regulatory frameworks, encouraging interdisciplinary collaboration, and advocating for ethical AI practices.

Conclusion:

The integration of AI technologies into healthcare systems holds tremendous promise for revolutionizing patient care, improving efficiency, and reducing costs. Real-world applications such as IBM Watson's diagnostic capabilities and the use of AI assistants like Cortana and Alexa in hospitals demonstrate the tangible benefits of AI in augmenting medical staff and enhancing patient experiences. From predictive analytics for operational efficiency to virtual nursing assistants for patient support, AI-driven solutions are transforming every aspect of healthcare delivery. However, alongside these opportunities come significant challenges that must be addressed to ensure the responsible and equitable deployment of AI in healthcare. Accountability for system use, trust issues, cybersecurity concerns, loss of managerial control, and potential job displacement are critical considerations that demand thoughtful governance frameworks and ethical guidelines. Balancing innovation with accountability requires collaboration among policymakers, healthcare providers, technology developers, and regulatory bodies to establish robust standards for AI use in healthcare. Moreover, addressing the "AI divide" and ensuring patient trust in AI systems necessitates transparent communication, education, and the integration of AI-related training into medical curricula. By fostering understanding and trust among patients and medical professionals, healthcare organizations can maximize the benefits of AI while minimizing resistance to adoption. Additionally, safeguarding data privacy and security is paramount to maintain patient trust and comply with regulatory requirements. Collaborative approaches such as federated learning offer promising solutions to leverage data insights while protecting individual privacy. In conclusion, the transformative potential of AI in healthcare is undeniable, but its successful implementation requires a multidisciplinary approach that prioritizes ethics, transparency, and collaboration. By addressing challenges proactively and leveraging AI technologies responsibly, healthcare systems can unlock new frontiers in patient care, research, and public health, ultimately improving outcomes and advancing the well-being of individuals and communities.

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