Niger. J. Physiol. Sci. 39 (June 2024): 1 – 8
www.njps.physiologicalsociety.com

Niger. J. Physiol. Sci.

Full length Research Article

The Role of Artificial Intelligence in Health Care

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Summary: Artificial intelligence (AI) plays a leading role in transmuting the field of healthcare. Numerous aspects of AI have been incorporated into the healthcare delivery system. For instance, in disease diagnosis, the practice of personalised treatment plans and precision medicine are AI-dependent. This review gives a widespread role of AI in healthcare, with a focus on applications, and challenges. Deep brain stimulation, statistical analysis, machine learning, and deep learning are a few examples of AI-powered technologies that have contributed immensely to biomedical research and medical imaging advancement. Moreover, AI algorithms are pivotal in genomics research, easing the identification of genetic markers related to disease vulnerability and treatment reaction, thereby aiding the practice of precision medicine. Apart from diagnosis and treatment strategies, AI assists in healthcare management and resource optimization, along with the discovery and therapy of drugs. Forecasting of disease outbreaks, effective allocation of hospital resources, and management of patient traffic rely mostly on predictive analytics driven by AI. Again, AI-powered virtual health assistance, telemedicine has aided patient appointments and support, giving real-time support and health recommendations. Although AI algorithms provide outstanding breakthroughs in healthcare, AI adoption is cumbered by numerous dares such as monetary concerns, regulatory hurdles, data privacy fears, and ethical considerations associated with AI applications, such as algorithm bias and transparency. Futuristically, AI application in healthcare holds vast potential, such as early disease detection, drug discovery, and optimization of treatment. Concerted efforts targeted at tackling the prevailing challenges and creating holistic control would be important to tie together the full potential of AI in rejuvenating the healthcare delivery system.

Keywords*: Artificial Intelligence, Healthcare, Personalized medicine, Precision medicine, Disease Diagnosis, Treatment Plans*

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Manuscript received- April 2024; Accepted- May 2024

DOI: https://doi.org/10.54548/njps.v39i1.1

INTRODUCTION

According to the Merriam-Webster dictionary, healthcare refers to “efforts made to maintain, restore, or promote someone's physical, mental, or emotional well-being especially when performed by trained and licensed professionals” (Merriam-Webster, 2023). Healthcare involves making sure that we are kept running as a singular being, with each organ and system working the way they are expected to because if there is a problem with one, there is a problem with all. Due to how broad the human body is, healthcare can be divided into various sectors, each focusing on specific areas. Such include pharma/biotech, health tech/medical devices, providers (doctors, nurses, physical therapists), and so on (Ridley, 2022). Each sector and others make sure that an individual is provided the best care possible but as time goes on, innovations have to be made and we have to conform to bigger changes. That is where Artificial Intelligence comes in.

Artificial intelligence (AI), which can also be known as machine intelligence, refers to a computer system’s ability to learn from given data and convert it (all on its own) into comprehensible information (Laskowski and Tucci, 2022). The term AI is often used to describe a computer that mimics cognitive processes that occur in the brains of humans throughout problem-solving and learning (Lund *et al*., 2020). It explains that AI has the ability or the potential to act in the way a human would when trying to complete basic tasks, calculate mathematical formulations, and even provide new information not known to man. Current use of this is in the healthcare delivery system, as well as, the discovery and design of drugs (Harrer *et al*., 2019). An excellent example of this is the computational modelling based on AI and machine learning (ML) principles and it can be a good tool for identifying and validating chemical compounds, identifying targets, synthesizing peptides, evaluating drug toxicity and physiochemical properties, monitoring drug efficacy and effectiveness, and drug repositioning (Zhong *et al*., 2018).

With the introduction of AI concepts, ML, and deep learning (DL) algorithms, virtual screening (VS) of compounds from chemical libraries containing over 106 million compounds has become simple and time-saving. Furthermore, AI models reduce toxicity issues that come from off-target interactions (Gupta *et al*., 2021).

Narrow Artificial Intelligence
A type of AI, known as artificial narrow intelligence (ANI) has been known to aim to improve the performance of a specific job, be it following weather updates, creating data science reports, or even planning games like poker or chess, its main function or ability is specific to a particle task, hence the name. As would be expected, it lacks the true ability to "think" like a human in terms of full consciousness and an awareness of oneself and various emotions attached to the decisions we make in our everyday lives. It cannot make a choice that involves placing one's emotions and feelings over logical reasoning and this could be counted as one of its flaws (Spiceworks, 2022). They might come off as complex and intelligent, but they are lacking in the core presets and characters that make human intelligence superior to any other kind. Examples include Google Translate, Google Assistant, Siri, and other natural language processing software. While these tools can communicate with us and process and grasp the language we use, they are classified as weak AI because they lack the fluidity and flexibility required to think for themselves like humans do. In other words, this AI system can't function on its own. The benefits of this form of AI include faster decision-making because they process information as well as complete tasks much faster than humans, relieving humans of many tedious, routine, and mundane tasks, and serving as a basis for the eventual creation of further intelligent AI variations such as general AI as well as super AI (Spiceworks, 2022).

Artificial General Intelligence
A more complex form of AI is artificial general intelligence (AGI), which, unlike ANI, enables a computer to perceive, learn, and execute intellectual activities similar to humans (McLean *et al*., 2021). This makes it more advanced in the sense that it can allow machines to simulate the way humans think and act and can also tackle any type of complicated issue thrown at it. These machines are hypothesized to function identically to humans since they are meant to have complete understanding as well as cognitive computing skills (Fjelland, 2020).

AGI is built upon the theory of mind AI paradigm and the hypothesis of this mind-level AI is concerned with teaching robots how to understand and comprehend human behavior and the fundamental features of consciousness. With such a solid AI basis, AGI can plan, make judgments, have cognitive abilities, deal with uncertain situations, and use past information in decision-making to increase accuracy. AGI enables robots to do novel and inventive tasks (Kanade, 2022a).

As of 2024, the AGI system is merely a product of science fiction as no form of this system exists but we believe that if they were ever to be created, they could function almost identically to humans, or even better than it would have a larger capacity to acquire and analyse massive data sets. Its capabilities could span from innovation, and perception of stimuli, all the way to natural language understanding and even mobility. Researchers also have predicted that AGI systems would have a higher level in terms of capabilities that involve the ability to handle multiple kinds of learning as well as algorithms, create rigid frameworks for all tasks, understand symbol systems, use different types of knowledge, understand belief systems, engage in metacognition, and apply metacognitive knowledge (Lutkevich, 2022).

Artificial Super Intelligence
Another hypothetical AI is known as the artificial super intelligence (ASI) which can potentially outperform even the capabilities of AGI by demonstrating cognitive capabilities and developing its thinking abilities. Often known as super AI, it is regarded as the most sophisticated, powerful, and intelligent sort of AI, surpassing the intellect of some of the world's finest brains (Kanade, 2022b).

These machines are supposedly self-aware and are capable of abstracting and interpreting concepts that humans cannot. What makes them distinct is the fact that they could perceive and comprehend human experiences and feelings which cannot be said of the two other types. Depending on the AI's cognitive capabilities, it can develop its sense of emotions, beliefs, and wants. Due to these unique skills, it could potentially have applications in almost all areas of human interest and can execute any things that humans can. They have been projected to make more precise decisions and solve problems than humans (Kanade, 2022b). At present, superintelligence is a hypothetical potential rather than a practical reality, as most computer science research is focused on ANI but it is sure that the world would definitively benefit from the implementation of such a powerful AI technology (Vishaal, 2023).

Deep Learning Models
Deep learning models (DLMs) employ what is known as artificial neural networks (ANN) to conduct complex computations on massive volumes of data. The reason they do this is that ANNs can imitate how the brain computes information. This sort of machine learning greatly relies on the functionality and operation of the human brain and its algorithms instruct computers to gain from examples fed into them. This makes DLMs a perfect fit for sectors such as healthcare, e-commerce, entertainment, and advertising. During training, algorithms extract features, organize objects, and uncover relevant data patterns by utilizing unknown components in the input distribution (Biswal, 2024). Deep Learning methods include convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), multilayer perceptrons (MLPs), deep belief networks (DBNs) and can deal with nearly any type of data and require a lot of processing power and knowledge to tackle complex problems (Mohapatra, 2022).

Applications of AI in healthcare
As mentioned previously, certain aspects of AI play a leading role in transforming the field of healthcare and its delivery system. Its models and algorithms help in areas such as disease diagnosis, personalised treatment places, health and genetics research (Figure 1), and much more as will be discussed (Davenport and Kalakota, 2019).

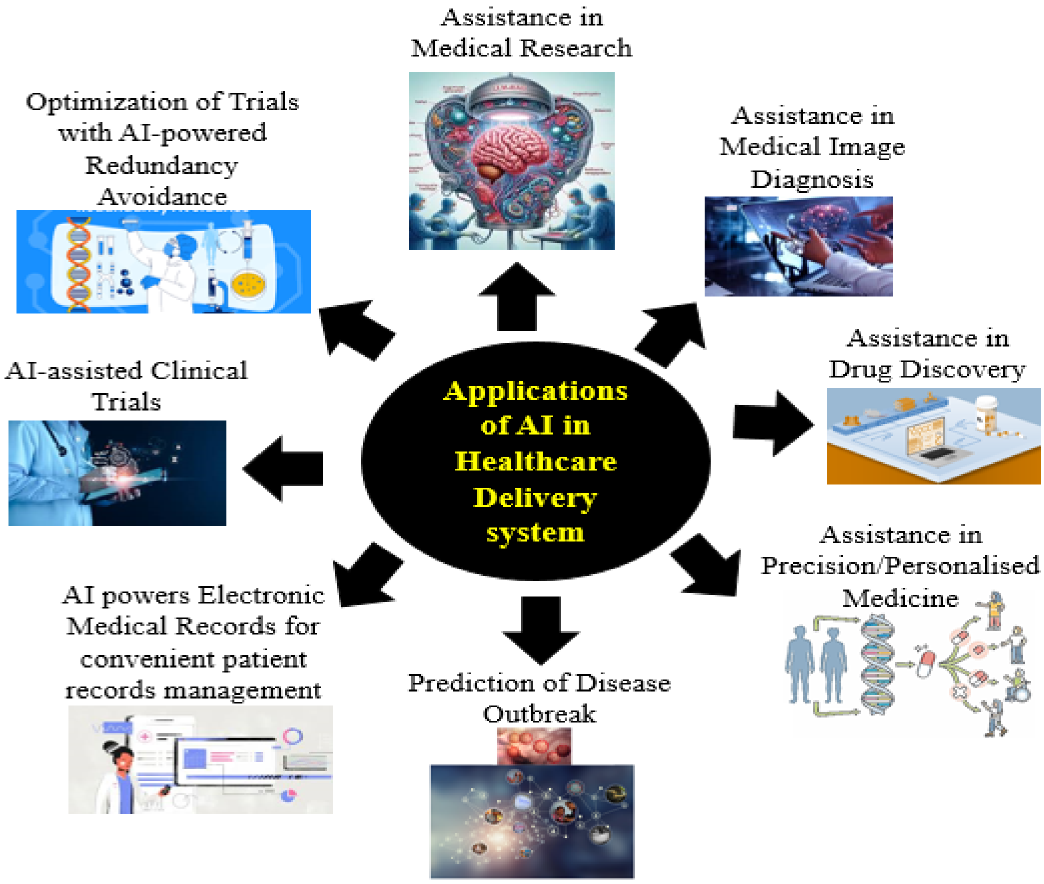

Figure 1:
Applications of Artificial Intelligence in Healthcare Delivery System (Adapted from Pandya *et al.*, 2021)

Diagnosis and Early Detection
Concerning the aspects of diagnosis in healthcare, AI has succeeded tremendously in breaking barriers regarding the screening and treatment strategies of various illnesses and disorders plaguing mankind (Davenport and Kalakota, 2019). Researchers have been able to implement AI models that can improve the prognosis of conditions such as cancer as shown by Mitsala *et al.*, (2021). Their research focused specifically on colorectal cancer and how the assistance of AI in the detection of colorectal polyps and optical diagnosis in colonoscopy can help doctors make more accurate diagnoses. Genetic testing also plays a good part alongside AI as shown by Hu *et al.* (2015). They conducted a simulation experiment using gene expression to categorize various colon cancer patients with the I into two groups: relapse and no relapse after surgery (Hu *et al.*, 2015). The researchers examined the classification accuracy of three neural networks: S-Kohonen (91%), Back-propagation (66%), and SVM (70%), and proposed that the S-Kohonen neural network is more suited for colon cancer categorization. Some researchers were also able to use gene markers in other to equip predictive models with the ability to measure the rate of disease survival, chemotherapy response, and even a re-occurrence of the cancer (Mitsala *et al.*, 2021)

AI technologies are also expected to help healthcare practitioners improve diagnostic accuracy and specificity (Mitsala *et al.*, 2021). Medical fields that use pictures for diagnosis, such as radiology, are particularly suited to AI-aided diagnosis. ML is effective at detecting abnormalities in photos. It has been hypothesized that what would take an expert radiologist 30 years to master radiology-pathology correlation might require an AI system hours or days to assess and learn in the future. As AI systems improve and are proven trustworthy in visual diagnosis, clinicians in the diagnostic fields may find it less essential to read photos, possibly only doing so on rare occasions (Stanfill and Marc, 2019).

There are other factors to consider, including whether the reporting of diagnostic specificity utilizing diagnostic test findings should differ based on the AI application (Jiang *et al.*, 2017). Providing precision based on AI findings may also rely on whether the AI application uses supervised or unsupervised ML approaches as unsupervised ML is well recognized for feature extraction, but supervised ML, which undergoes a training procedure to select the optimal outputs, is better suited to modelling predictions and is often regarded as providing more therapeutically meaningful outcomes. Hence, the sort of AI and the way the AI application is employed in the clinical workflow may influence subsequent reporting requirements for diagnostic code specificity (Jiang *et al.*, 2017).

AI can also help in the early diagnosis of possible or impending illnesses, allowing for more timely action. Machine learning algorithms are proven to be excellent at inferring particular health concerns and forecasting health occurrences. For example, methods based on neural networks are useful in identifying strokes (Jiang *et al.*, 2017). The algorithm's input variables include stroke-related signs such as arm or leg paresthesia, acute disorientation, visual changes, mobility issues, and so on. Additional instances include hospital readmissions, infections, and surgical complications (Bertsimas *et al.*, 2018; Saqib *et al.*, 2018).

Another good example is in the world of electrophysiology in healthcare. Wearable photoplethysmographic sensors have revolutionized the possibilities for arrhythmia screening by allowing long-term, passive measurement of pulse rate and regularity to detect an irregular pulse associated with arrhythmia (Mukhopadhyay *et al*., 2022). Beyond photoplethysmographic pulse detection, the Food and Drug Administration has certified Kardiaband and Apple Watch Series 4-5 to employ wearable ECG recording abilities for on-demand ECG validation of photoplethysmography-based arrhythmia identification (Feeny *et al*., 2020). On Apple Watch Series 4-5, irregular rhythm detection via photoplethysmography encourages the wearer to capture a single-lead ECG using the digital crown's sensor. The Kardiaband algorithm employs pedometer and photoplethysmographic sensors on an Apple Watch Series 2 or 3 to track heart rate and activity levels continually (Feeny *et al*., 2020). Other wearable devices powered by AI are summarized in Table 1.

Healthcare Management and Telemedicine

AI can also assist in the areas of healthcare management and resource optimization. This is significant as its effect could forecast disease outbreaks, cause effective allocation of hospital resources and even affect the management of patient traffic through its various analytics and models (Wang and Preininger, 2019).

Making healthcare records digitally accessible is an effective tool for remotely documenting and sharing healthcare information, and incorporating machine learning-based modelling designed specifically for administrative datasets can aid in the detection of potential complications, as well as improve healthcare resource utilization and outcomes on a personalised level (Lipkova *et al*., 2022).

Table 1:

Summarized table of common commercial smart wearables devices and their various cardiovascular clinical applications. BP, blood pressure; ECG, electrocardiogram; HR, heart rate; PPG, photoplethysmography; SaO2, oxygen saturation (Adapted from Boccuto *et al*., 2023).

Type of Wearable Device	Sensors	Measurements Available	Clinical Application
Earbuds	PPG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection Long QT diagnosis; HF management; Hypertension screening and management
Smart ring	PPG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Patch	ECG	Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Chest strap	ECG	Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Clothing and shoe sensors	ECG	Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Smartwatch	PPG; ECG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation. Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Smart band	PPG; ECG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation. Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management
Smart ring	PPG; ECG	HR; BP; SaPO2; cardiac output; stroke volume; rhythm and sleep evaluation. Single-lead and multi-lead ECG; continuous ECG-monitoring; QTc measurement; arrhythmia detection	Risk assessment and prediction; Cardiac telerehabilitation; Arrhythmia detection; Long QT diagnosis; HF management; Hypertension screening and management

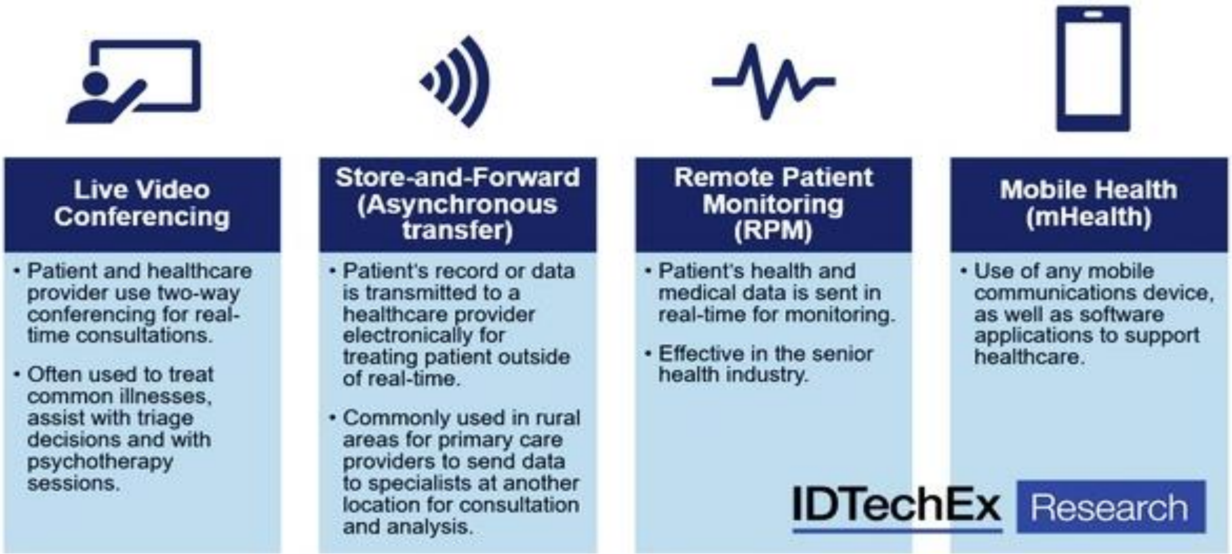

Figure 2:
Types of Telemedicine

One example is the use of machine learning on healthcare data to predict outcomes in sepsis patients. Samad *et al*. (2019) were able to achieve a 96% accuracy in predicting patient survival using echocardiography and digitally supplied data.

Its analytics, as noted, may also be employed in chronic disease management including the prediction of a disease outbreak, and might be characterized by multi-organ involvement, acute variable events, and extended illness progression latencies. One example is the use of predictive analysis in cases of retinopathy (Gulshan *et al*., 2016). Deep learning was used to train two validation datasets to detect and grade diabetic retinopathy and macular edema, and the results were highly specific and sensitive for detecting moderately severe retinopathy and macular edema (Gulshan *et al*., 2016).

Telemedicine is another sector of healthcare that can be positively affected by healthcare. Defined as the use of various communication technologies to form an interaction between and health practitioner and patient to discuss and send information concerning the diagnosis, treatment, and prevention of diseases in patients, it has been a tremendous help in cases of geographical distance between the two parties involved (Shen *et al*., 2021). This includes phone calls, virtual messaging, video calls, and data transfer systems (Figure 2). This has been mostly used in the field of ophthalmology, particularly in the case of diabetic retinopathy (Ting *et al*., 2018). Unfortunately, little research has been done into the potential relationship between AI and telemedicine, and the articles found mostly focused on hypothetical implications. An article focused on the usage of TOSCA, a telemedicine technology that allowed data to be sent between countries such as England and Denmark. The image analysis technique begins with picture polynomial transformation, which allows for blood vessel alignment, followed by preprocessing and retinal lesion extraction. Next, the picture was classified using supervised algorithms. Finally, the platform intends to create a normative reference database to assess algorithms and conduct additional research (Schneider *et al*., 2005).

Saeed *et al*. (2019) study laid out a cloud-based ophthalmic system for the Polish population. The system contained picture preparation, which involved converting the image to grayscale with a green channel, histogram stretching, medial filtering, and gamma correction. The steps involved extracting vascular patterns utilizing vessel segmentation and binarization, as well as removing vascular and optic discs (Saeed *et al*., 2019). Finally, pathogenic alterations were recognized and classed as healthy if no abnormalities were discovered. The published results are based on a 100-image dataset with 98% accuracy, 100% sensitivity, and 96% specificity in recognizing abnormal pictures. The suggested system demonstrated good sensitivity, specificity, as well as accuracy in the validation set (Saeed *et al*., 2019).

Drug Therapy and Discovery

Drug therapy is the treatment with any substance other than food used to avoid, diagnose, treat, or alleviate the symptoms of an illness or abnormal state (National Cancer Institute, 2011) and it is most well-known for aiding in disorders such as cancer, anxiety-related disorders, and depression and it offers patients high benefits of efficacy, minimal adverse reactions, and low drug resistance (Shabani and Hojjat-Farsangi, 2016). AI helps it to be more effective by making the identification of the best match for a given type of therapy less stressful. This is needed to reduce the risks of poor outcomes in terms of prognosis and the high costs of treatment. Despite the limited use of AI due to data unavailability, a study by Johannet *et al*. (2021) was able to show its gradual expansion using CNN models to predict responses to checkpoint immunotherapy in advanced melanoma patients.

To clarify the molecular mechanisms driving this type of therapy, interactome data may be organized and represented as network architectures, with components representing biological entities and edges representing associations/interactions among them (Zhang and Zhang, 2017; Song *et al*., 2022). AI biology analysis algorithms are an effective method for processing biological network data, and they can effectively address the complexity of illnesses caused by relationships among genes as well as their products in biological network structures, thereby improving our understanding of the root causes (Zhou *et al*., 2020). A very good example is in cancer target identification.

Network-based biology analysis applications begin by reconstructing networks by calculating molecular differential expressions and correlations (Hernández-de-Diego *et al*., 2018). Then, gene set enrichment analysis is used to find network modules that execute diverse biological activities. The found network modules are then utilized to identify important genes that might be targets of therapy (or biomarkers) for cancer (Hernández-de-Diego *et al*., 2018). WGCNA195 is a popular network-based biology analysis program that accepts numerous gene expression matrices as input. It then produces several gene network modules as well as the biological network's fundamental genes (You *et al*., 2022). Though network-based biology analytic approaches are valuable in discovering anticancer targets, they have several drawbacks, such as the inability to efficiently manage multiomics data, which results in high false-positive rates for discovered targets (You *et al*., 2022). AI has also been shown to predict drug efficacy as evident in a study done by Iloro *et al* (2016), which measured the responses of various cancer cell lines and showed that the models were able to almost perfectly predict the effectiveness of a drug. DL has also become a widely popular choice in terms of this subject as a study was able to show how easy the identification and prediction of drug efficacy by the deep neural networks, although there was a notable setback which was the inability of the model to properly interpret the biological mechanism driving such predictions (Chiu *et al*., 2019). This shows more gaps in the knowledge of AI and its relationship to pharmacology and there is a hope that more research will be done on this subject.

In terms of drug discovery, AI provides a quicker process of development and optimization of the design of drugs. Its usefulness in the aspect of pharmaceuticals can span from drug design, polypharmacology, chemical analysis, drug repurposing, and even drug screening (Sellwood *et al*., 2018). It can predict drug-protein interactions, design multitarget drug molecules, and even classify the targeted cells for drug delivery. A good example of this is the quantitative structure-activity relationship model (QSAR) which can predict large numbers of compounds within short periods and can also identify potential drug candidates (Paul *et al*., 2020). DLs also play a role as they can be implemented for evaluations of the safety and effectiveness of drug molecules based on data modelling and analysis (Zhu, 2019). Predictive models have also been shown to be able to predict the needed chemical structure of a specific compound (Pereira *et al*., 2016). All these various AI models can effectively change the way we view the production and discovery of pharmaceutical drugs.

Challenges And Future Directions

Improving the utilization of AI in healthcare in the rapidly evolving world is a huge issue due to increasing socioeconomic and environmental elements, as well as the advent of novel illnesses. However, we must understand the significant problems that might arise while leveraging AI's opportunities.

Monetary funding for AI is an important component in determining its usefulness. The achievement of AI technology development and application in healthcare systems is dependent on the availability of financing and budgetary assistance (Shaw *et al*., 2019). In underdeveloped nations with limited government funds, it is critical to assess the expenses and assets required for AI adoption, as well as the possible cost-to-care effectiveness ratio (Pongtriang *et al*., 2023).

Data mining becomes another critical component in improving this developing system with AI since it increasingly impacts policy choices. For example, patient data analytics are used for monitoring, prediction, and treatment planning to address health concerns in a variety of populations (Janett and Yeracaris, 2020). However, AI integration continues to encounter obstacles in terms of precision, patient confidentiality, and information security, as well as ethical issues. Furthermore, several countries suffer from data-related issues (Rajpurkar *et al*., 2022). These obstacles include a lack of experience in healthcare data mining, limited studies on AI's function in healthcare, and imprecise rules governing the application of machine learning in health and research.

In terms of ethical considerations, patients are more likely to trust a human caregiver than a computer, and healthcare staff are concerned about the susceptibility of AI to errors as a result of data breaches and cyber hacking. There are also crucial rules based on ethical values such as fairness, damage reduction, and justice that are lacking (Abdullah *et al*., 2021). A reassessment of these standards is required to enhance patients' and even medical practitioners' trust in the security and efficacy of AI, and patients should be offered the option of incorporating AI into their treatment care

Furthermore, data gathered by healthcare systems at the basic, secondary, as well as tertiary health service levels are ineffectively integrated due to the multiplicity of platforms utilized for health information collecting. This restricts the application of such databases for efficient care planning and coordination. As a result, government regulations must be modified to tackle the incorporation of AI in healthcare, as well as improve the effective use of medical data for prediction, investigation, as well as care planning, to achieve long-term outcomes (Jassar *et al*., 2022).

CONCLUSION

Incorporation of AI into healthcare constitutes a watershed moment with far-reaching ramifications. It has emerged as a transformational technology, changing how we perceive, analyse, and use various data relating to a patient’s health and well-being. AI uses machine learning algorithms, neural networks, and others to extract important insights from complicated biological systems, allowing for more accurate diagnosis, tailored therapies, and predictive interventions ((Jiang *et al*., 2017; Wang and Preininger, 2019; Johnson *et al*., 2020). Furthermore, AI-powered tools streamline research methods, boosting the rate of discovery and innovation in healthcare. However, ethical factors must be carefully addressed to guarantee that AI is deployed responsibly and equitably. Despite these challenges, AI's position in the health system is expected to grow and usher in a period of extraordinary medical discoveries. The use of AI is transforming healthcare by improving the accuracy and efficiency of diagnosis, developing new medical technologies, and helping with early treatment (Noorbakhsh-Sabet *et al*., 2019). AI has the potential to massively improve the way we view healthcare if ethical regulations are strictly followed.

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