Review Article

**The Role of Artificial Intelligence in Enhancing Healthcare**   
  
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## AI-Powered-Healthcare Solutions a b s t r a c t

This research explores the growing influence of Artificial Intelligence (AI) in healthcare, particularly in the context of online consultations and decision-making processes. The study compares trust in human doctors versus AI doctors, examining both cognitive and emotional trust dimensions. It is hypothesized that patients tend to place greater trust in human doctors and are more likely to adopt their health recommendations compared to AI doctors. Furthermore, the research investigates the role of personalization in AI healthcare systems. It is expected that AI doctors who tailor their advice based on individual patient circumstances will foster higher trust and improve the adoption of their recommendations.

In addition, the study examines the effect of empathy in AI doctors. AI systems that show emotional support during consultations are anticipated to build stronger trust relationships with patients, thereby increasing their willingness to follow AI doctors' advice. The research also delves into the interplay between cognitive trust, emotional trust, and the intention to adopt AI recommendations. Cognitive trust is proposed to positively influence emotional trust, which in turn mediates the relationship between trust and the intention to adopt AI-driven medical advice.

By integrating the importance of personalization and empathy in healthcare, this research aims to provide insights into how AI systems can be optimized for better patient engagement and trust. The findings contribute to the understanding of how AI can be integrated into healthcare in a way that balances both technological competence and emotional intelligence, ultimately enhancing the patient experience and improving adoption rates for AI-driven medical solutions.

# Introduction

Artificial intelligence (AI) refers to the capability of computers to emulate human intelligence. Its inception dates back to the 1950s, when it began as computer-based systems designed to replicate the problem-solving and decision-making abilities inherent to human cognition. Central to AI are mathematical modeling techniques that incorporate statistics, probabilities, and extensive databases. Initial AI frameworks relied on algorithms coupled with a set of predefined rules to draw inferences from given inputs [4].

However, over the past twenty years, AI has undergone significant transformation, moving beyond its foundational concepts. In contrast to traditional rule-based AI systems, modern methodologies such as machine learning (ML) analyze vast datasets to identify correlations and patterns [1]. For example, an ML model can be trained to detect breast cancer from mammograms by processing a substantial collection of such images. These models can operate in a semi-autonomous or fully autonomous manner, learning from data without requiring explicit programming for every procedural step by a human operator [6]. Deep learning (DL), a branch of machine learning, utilizes artificial neural networks (ANNs), which are sophisticated algorithms that progressively identify features from unstructured data, including documents, images, and text [3].

In the past decade, advancements in ML technology have significantly improved "perception," which involves the interpretation of sensory data. This technology emulates

human perceptual abilities, allowing machines to recognize objects, comprehend speech, and interpret visual and auditory information [5]. Such developments have resulted in remarkable progress in computer "vision" and natural language processing, tasks that were previously exclusive to human capabilities [2].

Nevertheless, the most effective ML systems often function as "black boxes" for end-users, making it challenging to analyze, clarify, or comprehend the reasoning behind their outputs. A considerable portion of the advanced AI applications in the healthcare sector relies on these complex systems.

While medical AI tools have been present in the market since the 1990s, their prevalence has surged significantly over the past decade. This growth can be attributed to recent advancements in AI research, the vast amounts of healthcare data available for algorithm training, and the remarkable increase in computational power, as anticipated by Moore's law. A substantial portion of these applications, exceeding 75%, pertains to radiology [1].

AI systems are now capable of executing a diverse range of tasks across various clinical specialties, including critical care, robotic surgery, and mental health. They serve multiple functions such as information synthesis, clinical decision support, population health initiatives, business analytics, and enhancing patient engagement [3]. Additionally, AI applications are revolutionizing primary care through tools designed for automated symptom assessment, triage, and referrals. Recently, they have also proven effective in global health contexts by predicting and monitoring infectious disease outbreaks [6].

Despite the seemingly advanced nature of AI, many individuals are already utilizing it in their everyday lives, such as on e-commerce platforms, streaming services, digital gaming, email filtering, and voice recognition technologies like Alexa and Siri [4]. Healthcare innovations, including AI-enabled smartwatches that monitor ECG, blood pressure, blood sugar, blood oxygen levels, and even detect falls, are widely accessible. When integrated with telemedicine and wearable monitoring devices, AI has significantly enhanced senior living and home care for patients [2].

The potential of AI in healthcare can be further understood through various examples of its application across clinical, non-clinical, and non-machine domains [5]

# Section-I

### What is artificial intelligence?

Artificial intelligence (AI) refers to the capability of computers to emulate human intelligence. Its inception dates back to the 1950s[3], when it began as computer-based systems designed to replicate the problem-solving and decision-making abilities inherent to human cognition. Central to AI are mathematical modeling techniques that incorporate statistics, probabilities, and extensive databases. Initial AI frameworks relied on algorithms coupled with a set of predefined rules to draw inferences from given inputs. However, over the past twenty years, AI has undergone significant transformation, moving beyond its foundational concepts[40]. In contrast to traditional rule-based AI systems, modern methodologies such as machine learning (ML) analyze vast datasets to identify correlations and patterns. For example, an ML model can be trained to detect breast cancer from mammograms by processing a substantial collection of such images. These models can operate in a semi-autonomous or fully autonomous manner, learning from data without requiring explicit programming for every procedural step by a human operator. Deep learning (DL), a branch of machine learning, utilizes artificial neural networks (ANNs), which are sophisticated algorithms that progressively identify features from unstructured data, including documents, images, and text.

In the past decade, advancements in ML technology have significantly improved "perception," which involves the interpretation of sensory data. This technology emulates human perceptual abilities, allowing machines to recognize objects, comprehend speech[32], and interpret visual and auditory information. Such developments have resulted in remarkable progress in computer "vision" and natural language processing, tasks that were previously exclusive to human capabilities.

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### AI in healthcare

Although medical AI tools have been in the market since the 90s, the number has increased manifold in the last decade. This is due to the recent advances in AI research, the massive amounts of healthcare data now available to train algorithms, and exponential increase in the power of computational hardware (as predicted by Moore's law). The vast majority (>75%) of these applications are related to radiology.1 AI sys-tems can now perform a wide variety of tasks across clinical specialties from critical care to robotic surgery and mental health. They can be used for information synthesis, clinical decision support, population health interventions, business analytics, and patient engagement. AI applications are also transforming primary care with tools for automated symptom checking, triage, and referral. In recent times, they have also been used quite effectively in global health to predict and monitor infectious disease outbreaks[26]

Although AI may sound exotic, most of us are already using it in some form in our daily lives e.g. on e-commerce sites, online entertainment platforms, digital games, email filters, voice recognition (Alexa/Siri), etc. Healthcare applications like AI-enabled smartwatches, which can monitor ECG, BP, blood sugar, blood oxygen levels, and even falls, are commonly available too. Combined with telemedicine and wearable de- vices for monitoring, AI has transformed senior living and home care of patients.

We can further appreciate the capabilities of AI in health- care through some examples of their application in clinical, non-clinical, and non-machine domains.

### Improving clinical performance

Many studies have shown that AI tools significantly improve accuracy, efficiency, and speed in the execution of medical processes.7 AI tools for screening diabetic retinopathy images have proven to be just as accurate as humans and can give results typically in 30 s or less.8 Similarly, AI has been used to screen for tuberculosis with impressive accuracy from chest radiography in a process time of about 20 s.9 Thus, besides improving accuracy of case detection, these tools also enable early initiation of treatment.

AI tools have been demonstrated to predict future medical risks which can significantly reduce morbidity and mortality. Studies have shown that AI tools can pick up breast cancer risk up to five years in advance.[10]AI tools have been able to identify new patterns on ECG that could predict the risk of sudden cardiac arrest in the future. As most cases occur out-of- hospital and can be fatal within minutes, the prospects of preventing such fatalities through AI predictions are immense.

### ‘Non-machine’ domains

### None clinical applications

AI has transformed the pharmaceutical research by showing new ways of drug discovery. Halicin, a new broad-spectrum

antibiotic, was discovered by researchers at MIT using AI. While traditional methods can take many years for the pro- cess, the MIT team discovered the molecule in a matter of days by using deep learning tools [4]

Business and non-clinical applications of AI are being used effectively in administrative tasks such as appointment scheduling, answering patient queries and screening calls and emails, business analytics, and insurance approvals. For

instance, an AI model for scheduling appointments in radi- ology demonstrated a 71% reduction in patient wait time from 7 days to 2 days for CT and MRI appointments and improved utilization of the facilities.15 Health insurers use AI to gather, analyze, and utilize large volumes of healthcare data to identify new business opportunities, optimize risk management, improve billing, and provide more personalized services. AI medical documentation tools use ML and natural language

processing to help physicians with the mundane, time- consuming task of documentation by automatically filling up Electronic health record (EHR) forms from doctor-patient con- versations. They are also used for auto-generating radiology reports from X-rays, CT, and MRI scans.

# Section-II

The implementation of technology in healthcare is fundamentally a human-centered issue rather than a purely technical one. It requires meticulous and careful management, as any errors could result in significant harm and serious consequences. The ethical considerations of artificial intelligence (AI) in healthcare extend far beyond the principle of primum non nocere ("first, do no harm"). These concerns encompass issues of equity, access, and autonomy, often introducing accelerated risks and challenges that may not yet be fully understood.

### Safety and reliability

Epic Sepsis Model is an AI tool used at hundreds of US hos- pitals for predicting sepsis. It is part of Epic's electronic med- ical record software, which serves 54% of patients in the United States. A study using data from 27,697 patients at the University of Michigan found that Epic Sepsis Model missed most instances (67%) of sepsis and produced multiple false alarms. A larger study using data of over 77,000 patients found[45]

that the model’s accuracy at predicting sepsis was “no better than a coin toss”. [20]Bearing in mind that sepsis is a life- threatening emergency, these findings raise serious con- cerns about the reliability of such an AI-based system.

During the COVID-19 pandemic, hundreds of clinical pre- diction models were developed and deployed. However, The Alan Turing Institute, UK’s national institute for data science and AI, found that, when subjected to rigorous scrutiny, none of them showed any valuable clinical impact. Another sys- tematic analysis of 731 published prediction models for the diagnosis and prognosis of COVID-19 found that none could be recommended for clinical use[27].

Radiology has the maximum number (76%) of FDA- approved AI applications in the USA. However, a study found that 94% of AI systems that scanned for signs of breast cancer were less accurate than the analysis of a single radiologist, and all were less accurate than the consensus of two or more ra- diologists. In one of the studies, it was found that the AI tool screened out 10% of cancers detected by radiologists [20]The clinical and economic impact of these false negatives, and their legal liability, brings into question the utility of such tools.

Early and accurate diagnosis of heart attack is vital to successful treatment and better outcomes. However, doctors can be subjective, even miss a heart attack if the patient is a woman[26].AI tools are supposed to be more objective, but a study in British Medical Journal (BMJ) noted that an AI-based app alerted for heart attack

when used for a 60-year-old man with chest pain, but when used for a 60-year-old woman with identical symptoms, it concluded that she was having a panic attack.[31]

In recent years, generative AI (GenAI) tools, such as ChatGPT, have captured significant attention due to their vast potential across numerous fields. These tools are being explored not only for assisting in the development of research topics but also for supporting clinicians in diagnostics and providing virtual assistance to patients. Moreover, both clinicians[32] and students can derive substantial benefits from the real-time updates these tools can offer on emerging developments in healthcare and other sectors.

However, a critical issue with GenAI tools is their susceptibility to "hallucinations," a phenomenon where these systems generate information that, while contextually coherent and syntactically correct, is factually inaccurate. More troubling is the fact that such false outputs are often presented in a manner that is highly persuasive, creating the illusion of validity. In the medical field, this type of misinformation is particularly perilous, with potential consequences not only for patient safety but also for medico-legal matters that could While the examples provided here are not exhaustive, they underscore the real-world challenges clinicians face when integrating AI tools into clinical decision-making.[21] These limitations necessitate a high level of awareness among healthcare professionals, as inaccurate inferences or recommendations derived from AI systems can result in severe and irreversible harm to patients.

### Equity and fairness

AI, being non-human, comes with a sheen of objectivity, an allusion to fair and unbiased handling by removing human subjectivity. However, there are numerous examples of bias from the use of AI tools in fields as diverse as education, in- surance, HR, finance, and even the judicial system

.[28 -29]Healthcare is equally susceptible to it.

Bias may be understood as a prejudicial or unfair prefer- ence toward certain groups or ideas. When we consider a technology for assisting in diagnosis or treatment, an impor- tant factor is whether it would perform equally for all patients. Any bias in medical AI tools can have striking implications for

people who are historically disadvantaged due to race, ethnicity, gender, or socioeconomic status, subjecting them to inaccurate treatment recommendations, delays, or even denial of essential and urgent medical care. An AI tool widely used in US hospitals to predict the need for additional medical care was found to grossly favor White patients over Blacks. Correcting for the bias was found to substantially increase the percentage of Black patients receiving additional care (from 17.7% to 46.5%). Considering that the system was in use for several years in one of the largest healthcare systems in the USA, one can appreciate the magnitude of its long-term impact[28]

### Sources of bias in AI

A systematic review of the impact of unconscious racial prejudice amongst physicians found that White patients are more likely to receive thrombolysis, a life-saving treatment, for heart attacks. Another study noted that 74% of White pa- tients receive painkillers for fractures as compared with only 57% of Black patients in the emergency department. Amongst children with appendicitis, Black children have been found to be less likely to receive opioid pain medication compared with White children (12% versus 34%)

[32]

These practices in diagnosis and treatment are captured in datasets, and get reflected downstream because the same historical datasets are used to train AI models. So, although AI systems are inherently secular and, being non-human, ex- pected to be more objective, it is difficult to eliminate bias from AI because these models are trained on data from the real world. These data, directly or by proxy, can carry along trails of existing societal inequities and discrimination.

Another source of bias is the lack of diversity in the training data. Studies have demonstrated that imbalances in the training datasets lead to dramatically lower accuracy of di- agnoses from chest radiography for women and Black peo- ple [14 - 35] Similarly, AI models for identifying skin cancer are less accurate in dark-skinned patients because the models are mostly trained with light-skinned subjects. The latter is not by design though; a review of publicly available dermatological datasets found that 79% of the images originated from Europe, North America, and Oceania, with substantial under- representation of darker skin types.36,37 AI models trained on such skewed data clearly lack generalizability to other populations, leading to poorer outcomes for unrepresented or under-represented groups.

Bias can also enter healthcare AI through the assumptions

made by the people who create them. A clinical tool commonly used in the USA was for predicting the success of vaginal birth after caesarean delivery. It was noted that the tool incorporated a race correction for Black and Hispanic women, which contributed to the inference that they were less likely to have a successful vaginal delivery than White women. This led doctors to perform more C-sections on them, exposing them to unnecessary surgical risks. Similarly, American Heart Association's Guidelines for Heart Failure Risk Score, through a race correction, categorizes all Black persons as being at a lower risk. This puts them at a lower priority for receiving emergency care and specialist referrals.38

While most bias may stem from data, assumptions, or subjectivity, it could even be induced voluntarily. Research has demonstrated that DL models can be trained to predict

race from medical images. This could potentially pose a serious threat to fairness in healthcare[39]

Clearly, instead of helping to remove avoidable disparities, AI can worsen them for sections of the population who are already at a disadvantage. We must ensure that AI applications in healthcare are not only accurate, but also fair and just. Guardrails in the form of regulations and policies for develop- ment of AI tools, diversity-equity-inclusion-focused approaches and user involvement are crucial for mitigating AI bias.[20]

# Section-III

### Artificial intelligence and medical ethics

Medical ethics is an inherent and inseparable part of health- care. It describes the obligations of physicians and health care organizations to patients and the community. Various in- terpretations of medical ethics can be traced back to ancient history and later through the times of Charak and Hippo- crates. In modern times, the framework of four core principles viz[15]. autonomy, non-maleficence, beneficence, and justice, is widely accepted in healthcare. In this section we examine the ethical issues arising from the use of AI in healthcare and evaluate them against the ibid framework.

### Beneficence and non-maleficence

The priniples of beneficence and non-maleficence reflect the Hippocrtic principle of “to help and do no harm”. Benefi- cence, i.. to use medicine for the benefit of the patient, is fundametal to the responsibility of a physician toward a patient. I creates an obligation for the physician to act in the patient’s best interest. Non-maleficence, on the other hand, indicates that no harm is likely to be caused by medical in- terventions. Although non-maleficence may seem to be a corollary of beneficence, [15]it is essentially complementary, and is often taken to primacy as in the dictum “First, do no harm”. Together they indicate that medical actions must have a reasonable expectation of benefit to the person, and expected risks should be balanced against expected benefits.

Although AI has immense potential to increase benefi- cence, the evidence at present isn’t robust enough. As noted in the previous section, there are significant concerns relating to the safety, accuracy, and reliability of AI tools. Incorrect di- agnoses, false negatives, inappropriate treatment recom- mendations and potential for misinformation indicate the need for caution. Furthermore, as most of the applications of AI in the healthcare field are based on ML,[34] the opacity in their decision-making is also a cause for concern. The inability to see the rationale behind the AI decision, or query it when in disagreement, makes it difficult to provide a reliable or trust- worthy environment for the patient.

### Justice

In ethics, justice implies having systems to ensure the fair dis- tribution of resources and benefits across the entire population. These include allotment of scarce resources like equipment, diagnostics, medicines or transplants. For instance, when there are limited ICU beds, the principle of justice requires that pri- ority for ICU admission be based on only clinical parameters,

irrespective of race, ethnicity, or socioeconomic status. The emphasis is on treating all persons equally and fairly.

It is often believed that the greater use of technology would put an end to unfairness by removing human subjectivity. The mathematical nature of AI and the inanimate form of technology generates a false sense of objectivity of AI tools. It is essential to understand that bias is part of the DNA of AI as the data they are trained on carries the trails of existing so- cietal inequities, incorrect assumptions, and human subjec- tivity. Rather than supporting the cause of justice in healthcare, AI can aggravate, accelerate, and multiply the embedded societal inequities and historical injustices.[23]

Although AI bias is an extension of existing social in- equities, there is a significant difference-the latter may be subjective and sluggish, whereas AI bias is systemic and accelerated. Being based on feedback loops, these embedded biases often get amplified and perpetuate themselves through data cascades, causing even more negative downstream ef- fects. Because of their complexity and lack of transparency, such biases are even more challenging to identify, let alone

control. Alarmingly, their harmful effects are not limited to the individual level but can ripple into society at large, unde- tected, and at unprecedented scale and speed

Autonomy[34]

The maxim “Nothing about me, without me” captures the concept of autonomy very succinctly. In simple terms, au- tonomy means that every person has the right to make de- cisions related to their own body as also, by extension, their personal information (data). It respects their right to make decisions about their own lives. The concept of informed consent, which is the bedrock of shared medical decision- making, stems from the principle of autonomy.[24]

Informed consent is the process by which the physician apprises a patient about the risks, benefits, and alternatives

of a medical procedure, which, in turn, allows the patient to make a voluntary decision about whether to accept or refuse the treatment. The principle of autonomy obliges the physi- cian to disclose medical information and treatment options that are necessary for the patient to exercise self- determination. This requires the physician to have a com- plete and thorough understanding of the reasoning behind the diagnosis and treatment recommendation. However, due to the complexity and opacity of AI tools,[33] the physician has no means of understanding how the AI arrived at its diagnosis or recommendation. In such a scenario, the physician may not be able to truly administer an ‘informed’ consent. AI may, thus, inadvertently, relegate both, patients and physicians, to being passive participants in the medical decision-making process, sacrificing their autonomy in the process.[20]

Ironically, AI might aggravate physician's autonomy even

further; they might feel compelled to rigidly follow AI rec- ommendations to avoid any legal liabili

Conclusion

The development and integration of AI-supported applications in healthcare will only increase as technological advances continue to flourish. A full systematic review of AI in healthcare is needed. However, the rapidly evolving innovation and adoption of AI in healthcare makes this challenging. Many countries, including China, South Korea, and parts of Europe, have invested significantly in AI research and education, underscoring the urgent need for the United States to accelerate its efforts to remain competitive [18]. There are many applications of AI technology currently enhancing clinical practice with the goal to improve healthcare providers' job functions and promote safe patient care effectively and accurately.

For example, understanding how AI is revolutionizing pharmaceutical development will equip nurses to effectively collaborate with interdisciplinary teams and use AI-driven tools as healthcare providers. Nurses who are prepared to use AI-facilitated natural language processing to efficiently complete clinical documentation can spend more time engaging in patient care [19]. Leveraging technology can promote healthcare provider retention by delegating administrative tasks to AI applications and supporting the personalized and empathetic care that nurses provide. The foundational nursing principles of trust, caring, and compassion must be upheld with the uptake of AI use [20]. A workforce equipped with the knowledge and skills necessary to adapt to the ever-evolving landscape of healthcare delivery and competence in AI applications ensures the delivery of technology-supported high-quality patient care that maintains the patient at the center of care.

Additionally, to support the development of an AI-competent nursing workforce, nurse educators will need to be confident in their abilities to use AI applications in their educator role and prepared to integrate content and learning activities into the nursing curriculum. The advances of AI applications in the healthcare setting provide a glimpse into the capabilities of technological advances that will undoubtedly influence academic settings and support the implementation of competency-based education in nursing education. Furthermore, adequate preparation to ensure the ethical use of AI technology is needed to prevent bias and support privacy in the academic setting [21].

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