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HUMAN-AI COLLABORATION IN HEALTHCARE STUDYING THE IMPACT OF AI ON HEALTHCARE PROFESSIONALS DECISION-MAKING PROCESSES

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ABSTRACT
The emergence of human-AI collaboration can be attributed to the advancements that have been made in artificial intelligence (AI). The shortage of skilled healthcare workers might be alleviated through such collaboration in the healthcare industry, which would also help medical professionals who are working too much and improve the overall quality of healthcare. Nevertheless, there are still many challenges that need to be addressed, including the examination of biases in clinical decision-making, the distrust of AI, and issues with adoption. Even while there is a growing body of research on the topic, it is coming from all over the place, and our understanding of it is limited. This study does a literature analysis in order to address this issue. The purpose of this review is to assess previous research, identify gaps in the research, and offer future research possibilities. Our review found that few studies have addressed topics such as the increasing and dynamic nature of healthcare industry collaboration, the ways in which humans and AI complement one another, public opinion and understanding of AI, and its potential effects on both individuals and healthcare organizations in the future. Additionally, there is a need for additional research that is driven by theory in order to reap the benefits of collaborative artificial intelligence for healthcare and to shape its design, implementation, and application.

1. INTRODUCTION

Artificial intelligence (AI) has the ability to change health care practices [1,2]. AI was presented as a technology to improve decision-making in systems with complexity and ambiguity. Artificial intelligence (AI) is a new tool that can help in decision-making. The importance of humans is often overlooked when it comes to AI applications in the real world. The development of automated systems to help human decision-making began in the 1950s, coinciding with the establishment of the Fitts list, which specifies the complementary skills of humans and automated systems [3]. Eleven assertions on the Fitts list state that humans outperform automated systems in specific areas, such as processing speed, short-term memory, computing power, replication, and simultaneous operation [4]. All of these claims center on the idea that people have better senses than machines when it comes to things like detection, perception, judgment, induction, improvisation, and bodily memory retention. Based on the amount of human variables taken into consideration during system design, automated systems may or may not enhance human decision-making, according to multiple research [5].

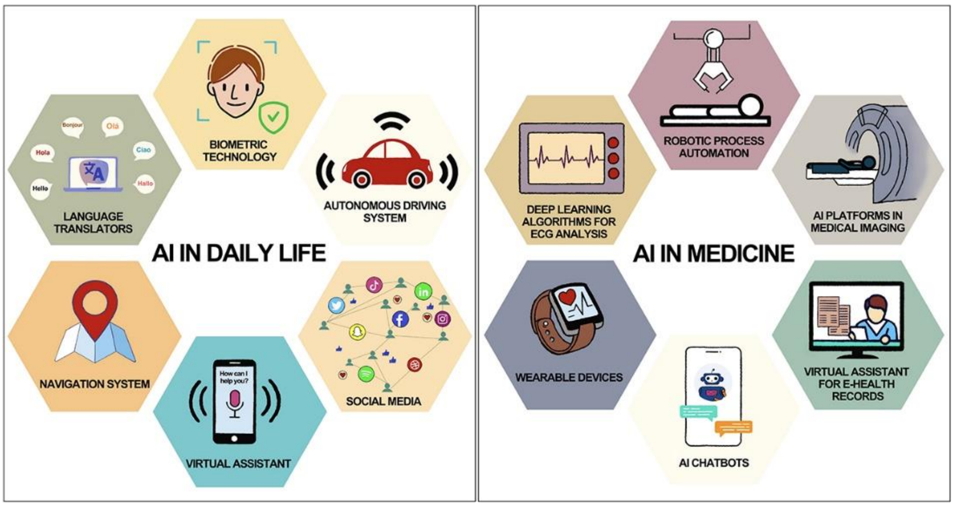

Figure 1. Common applications of AI in daily life and medicine.

The advent of sophisticated artificial intelligence (AI) systems might revolutionize many parts of human existence. It can automate activities, improve decision-making, and enable new sorts of interactions between humans and machines. The use of artificial intelligence (AI) is something that humans are continuously surrounded by and receiving assistance from in their day-to-day lives (Figure 1).

On the other hand, unlike other technologies, AI's method, functioning, and role have not been fully defined as of yet [6]. The lightning-fast progress of AI is to blame for this. Building trust is crucial in all kinds of human relationships, but it is particularly important in ones involving AI. In the healthcare industry, where patients' lives are on the line, it is absolutely critical to have a firm grasp on the trust dynamics that exist between humans and AI. We examine the effect of trust on the ever-changing relationships between AI and doctors in this research. In addition, we recognize important challenges and potential areas for future research in the health care domain, and we stress the essential features that control trust. Medical doctors, as domain specialists in healthcare, are the only ones this study will be addressing. This article primarily targets clinicians as customers of AI systems, while patients and insurance providers are also potential users. We are aware that the trust relationships between patients and insurance providers may be somewhat different from one another.

2. LITERATURE REVIEW

2.1 AI in Health Care

Artificial intelligence has shown a lot of promise in many areas of healthcare, including medical record mining, treatment plan design, robotics-mediated surgeries, clinical data interpretation, clinical trial participation, image-based diagnosis, preliminary diagnosis, virtual nursing, and linked health care devices [7]. Not only does AI have these uses, but recent attempts to regulate its use in healthcare and substantial expenditures in AI research indicate that it may soon be an indispensable tool for medical decision-makers.

AI research in healthcare has distinct obstacles when contrasted with research in other technical fields. The mathematical description of the underlying technical behavior in engineering applications is provided by physical system models. A major obstacle, however, is the absence of such quantitative models in several medical diagnostic applications (e.g., the exact correlations between illnesses and their causes). Clinicians' reactions to identical patient cases differ considerably. Given that clinicians' subjective answers include their own biases, it would be difficult to train AI-based technologies using these responses in the absence of ground truth. Additionally, AI studies need to take into consideration the fact that all health care applications have their own unique medical problem features. It would be impractical, for instance, to train an AI using a methodology developed for cancer applications and then apply it to cardiovascular problems. Not taking vulnerable groups into consideration while designing the AI system increases the risk that data from these populations will be underrepresented and that their demands will be unmet. This includes minority groups and people with disabilities. Each application's AI method may need to be tailored to the specific data kind and quantity, the population of interest, the data's variability and usefulness, and the sort of health care decisions that need to be made [8].

To add insult to injury, implementing adaptive AI technology that satisfies regulatory criteria is no easy feat in the highly regulated health care industry. The United States Food and Drug Administration (FDA) classifies software into three distinct types: (a) Software as a Medical Device (SaMD), (b) software that is integrated into a medical device, and (c) software that is used in the creation or maintenance of a medical device.... AI/ML-based Software, when intended to treat, diagnose, cure, mitigate, or prevent disease or other conditions, are medical devices under the FD&C Act and called Software as a Medical Device," explains the FDA in their definition of SaMD [9]. Breast cancer detection software, computer-aided detection tools, and smartphone apps for viewing radiologic images for diagnostic purposes are all part of SaMD. Several AI-based SaMDs with "locked" algorithms have been certified by the FDA; these algorithms are adaptive, but modifications to them require a human process [10]. The algorithms always produce the same output for the same input.

An adaptive algorithm, in contrast to the conventional SaMD model, can learn to alter its behavior on its own, without human intervention. Depending on the inputs, an adaptive algorithm may learn and update itself to provide varied outputs. Incorporating a trustworthy validation and verification strategy into the AI architecture is essential for achieving safe and dependable operation in the face of adaptive behaviors.

Two possible benefits to human performance exist in the application of AI to healthcare. One advantage AI has over humans is its ability to learn from large datasets, which can include electronic health records and other incommunicable repositories of unstructured information. By quickly extracting relevant information from either offline or real-time data, an effective AI system can help improve organizational performance and enable clinicians to make informed decisions in real-time. Second, AI systems are more accurate at carrying out tasks that have been previously defined. Artificial intelligence (AI) does not experience burnout like humans do; it may remain actively engaged in tasks at all times without lowering its performance. Complex procedures might be drastically altered by this AI function. One advantage of the Da Vinci robotic surgery system is its ability to more accurately imitate a

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surgeon's hand movements [11]. In addition, there are other AI applications that have demonstrated results that are on par with human decision-making. The artificial intelligence machine AlphaStar can outscore a human gaming expert, while the breast cancer detection tool LYNA uses pictures from lymph node biopsies [12].

Artificial intelligence (AI) has some constraints that could limit its use in healthcare and other sectors where human lives are on the line. Because AI systems operate best with structured data inputs, there is a limit to the kind of information that can be provided for medical choices. The ability of deep learning algorithms to automatically find a good mathematical representation in a dataset is limited to the type of input data that they have been trained for. For example, these algorithms can only handle medical picture data. Furthermore, AI systems typically do not possess "common sense," which renders them incapable of detecting blatantly obvious errors in data or judgments [13]. So, to get the most of what AI can do, we need an appropriate architecture for human-AI collaboration that combines the analytical and intuitive thinking of doctors with AI's computational power.

3. TRUST IN HUMAN-AI COLLABORATION

As AI develops further, it will be able to do more, including assist medical personnel with decision-making in ambiguous situations, rather than just automate mundane, well-defined activities. A healthy dose of trust, often called calibrated trust [14], is essential for AI to make good decisions in the healthcare industry. One important component in building user trust in rule-based software systems is their deterministic and relatively predictable character. In a deterministic system, the inputs and beginning state are all that matter for the final behavior. The notion of trust may take on new dimensions, though, due to the unpredictable character of AI, wherein the same input can cause an algorithm to behave differently in subsequent iterations. We outline several key aspects affecting trust in health care AI in Figure 1. We also discuss potential approaches to enhancing trust relationships and how these factors affect trust. Please be aware that the figure is not meant to present a complete inventory, but rather to draw attention to key points about the reliability of AI in healthcare settings.

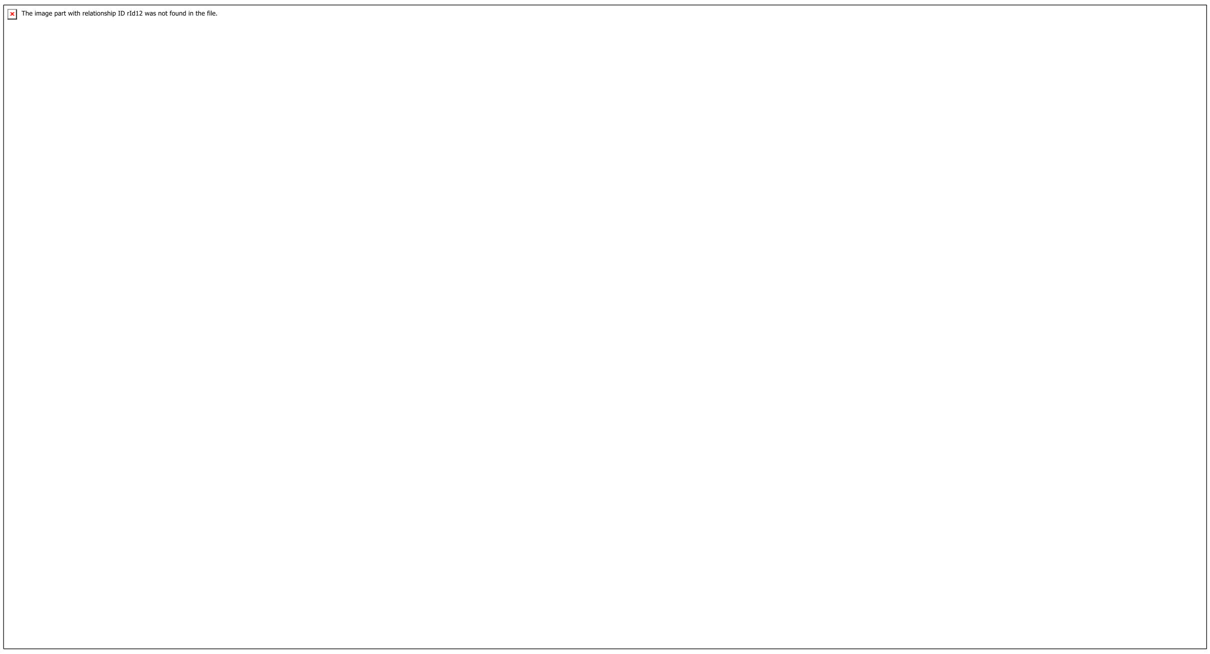


Figure 2.Human factors and trust in artificial intelligence.

The general public's mistrust of AI and similar technology is now a major barrier to their widespread use in healthcare. Users' level of trust in AI can be influenced by various human factors, including their level of education, past experiences, biases, and views towards automation. There are also a lot of AI system attributes, such as the model's complexity, controllability, transparency, and hazards. One of these factors that could be especially worrisome in the healthcare industry is the AI's dependability, which is defined as its capacity to regularly and predictably complete tasks [15]. This is because AI's dependability can alter when exposed to new data [16]. Both the user and the data they supply determine how trustworthy an AI system is. The clinical user might not even be aware that AI systems are biased or overfitted since they can be trained with subjective and insufficient data from different sources. Users are hesitant to trust and embrace AI systems because of these issues, which reduce the technology's performance [17].

Also, the greatest decisions made by a human-AI partnership could not be the ones that maximize the user's trust. At its most trusting, an AI system's recommendations and outputs are taken at face value by the user. The aforementioned constraints imply that an excessive reliance on AI can lead to disastrous outcomes, particularly in applications where human lives are at stake, even though AI can surpass human decision-making in certain contexts by integrating data from many sources. Thus, our research lends credence to the idea of ideal trust, wherein people and AI alike maintain a healthy dose of skepticism toward one another's decision-making processes, given that we are all fallible. How skeptical a user and their AI system need to be in order to make the best therapeutic decisions is entirely up to them. Incorporating techniques that create and maintain an optimal level of trust between the user and the AI system is crucial for AI development [18].

Building trust between humans and AI is difficult because of the inherent unpredictability of knowledge-based evolving AI systems. In our view, for AI to reach its full potential in terms of trustworthiness, it must prioritize openness, robustness, and fairness (Figure 1). Decisions made by algorithms are often believed to be more robust and equitable than those made by humans [19]. On the other hand, algorithms prioritize some factors above others due to their inherent bias. It is also possible for machine learning algorithms' characteristics to amplify preexisting data bias, which could have an adverse effect on members of legally protected groups due to factors like sexual orientation, gender, or color. Because it trained the model with less than 5% data from a dark-skinned population, a study [20] that employed machine learning to detect skin cancer may have been biased against dark-skinned individuals. Whether AI is fair depends on a lot of factors. These include the level of transparency offered, the users' expectations about how their data will be used (both clinical and personal data), and the effects of data processing on users (both care providers and patients). An AI system needs to be fair and also work to minimize prejudice. Disparities in the distribution of training data can lead to bias, which in turn can lead to unfair outcomes in predictions and classifications. Finding and reducing biases in validation and verification that result from physicians' subjective responses is essential for building fair AI systems.

4. ARTIFICIAL INTELLIGENCE FOR HEALTHCARE: APPLICATIONS

Using the topical dendrogram as a guide, researchers will build a development model based on four important characteristics. Artificial intelligence has revolutionized healthcare. Artificial intelligence has helped medical practitioners in several ways, including health information systems, medical imaging, predictive modeling and decision support, geocoding health data, epidemic and syndromic surveillance, and medical imaging [22]. This assistance has been provided by AI's advanced algorithms and a number of specialized applications. Researchers also used bibliometric analysis to identify the four most common macro-variables in the field; authors were then asked to utilize these as keywords. In light of this, the subsequent sub-sections will attempt to illustrate the argument regarding the applicability of AI techniques in the healthcare industry. These components are depicted in Figure 2 below.

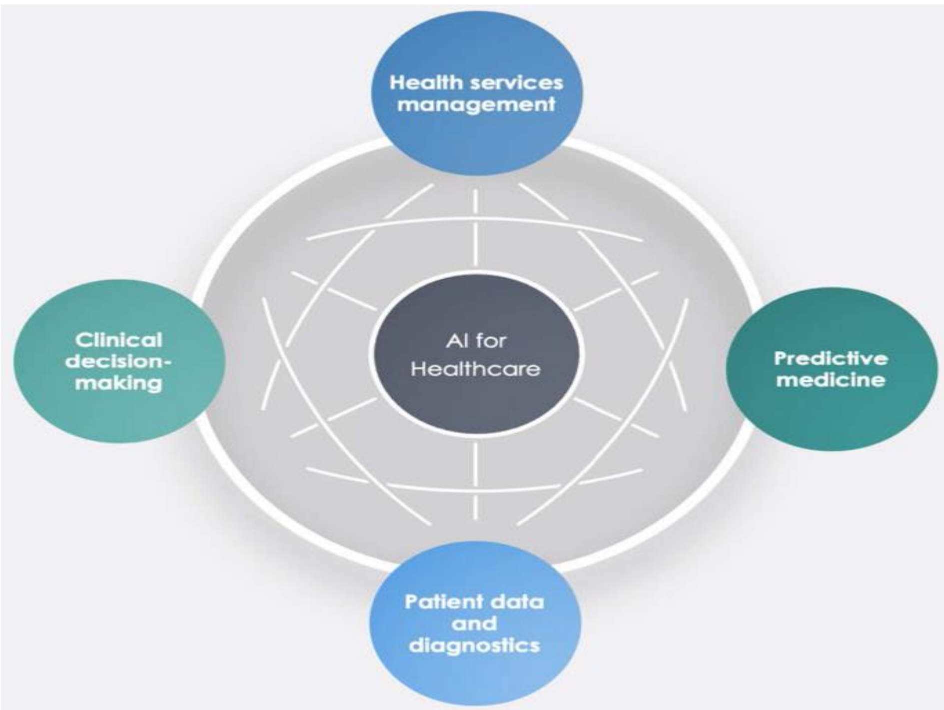


Fig. 3: Key aspects of artificial intelligence for healthcare.

4.1 Health services management

AI techniques have the potential to provide support for complete health care administration, which is one of the significant elements of these techniques. When it comes to their employment, these applications might be of assistance to administrators, nurses, and physicians. Using clinical practices, textbooks, and other publications as examples, an AI system can provide medical practitioners with continuous and perhaps real-time updates of medical information [23-30]. In the COVID-19 era, when successful global pandemic management necessitates constant information exchange, the power of these apps is growing increasingly more vital. In addition, there are applications that entail the coordination of information tools for patients and the facilitation of suitable conclusions for the purpose of health risk alarms and health outcome prediction (20). The following are some of the reasons why applications of artificial intelligence make it possible for hospitals and other health services to operate more efficiently:

- Data is immediately accessible to clinicians whenever they have a need for it.
- When it comes to the administration of medication, nurses have the ability to improve patient safety.
- Through communication with their medical teams while they are in the hospital, patients can maintain their level of engagement and be informed about their care.

Artificial intelligence also shows promise for making logistical operations more efficient. One use case is the just-in-time supply system, which relies on predictive algorithms to streamline the delivery of drugs and equipment. Captivating apps can also help with health services worker training. There is a potential that this evidence might help with the problem of closing the gap between rural and urban health care. At long last, the mountain of data stored in EHRs could be mined with the help of AI. Predicting data heterogeneity across hospitals and outpatient clinics, looking for outliers, running clinical tests on the data, bringing patients into a unified representation, improving models for diagnostic test prediction, and being transparent with benchmark data to analyze services provided are all ways to achieve this goal [31-37].

5. AI APPLICATIONS IN MEDICAL IMAGING

5.1 The Use Of AI In Analyzing Medical Images Such As X-Rays, MRIs, And CT Scans

With regard to the processing of medical images, AI systems have demonstrated impressive abilities. The ability to gather reliable and comprehensive findings based on these diagnostic scans is made available to healthcare professionals. Images from X-rays, MRIs, and CT scans can be processed by artificial intelligence in a substantially shorter amount of time. Because of this, trained experts can swiftly see trends, sift through mountains of data, and extract actionable insights.

5.2 The Role Of AI In Identifying Abnormalities, Tumors, And Other Medical Conditions

Through the use of medical imaging, artificial intelligence has showed an exceptional level of proficiency in recognizing and localizing tumors, abnormalities, and other medical concerns. In the case of cancer, the artificial intelligence algorithms are able to effectively evaluate large quantities of medical photos in order to identify and categorize certain cancers. Artificial intelligence medical diagnostic tools can help oncologists learn more about tumor stage, growth rate, and metastasis risk by comparing these results with historical data. This gives oncologists the ability to create individualized treatment programs.

5.3 The Potential For AI To Improve Diagnostic Accuracy And Efficiency

There is a great deal of untapped potential for medical imaging to provide a platform for artificial intelligence that improves diagnostic speed and accuracy. Medical diagnosis systems that are powered by artificial intelligence can be of assistance to radiologists by providing a variety of perspectives, reducing the likelihood of erroneous interpretations, and improving diagnostic accuracy overall. Additionally, it has the capability to accelerate image analysis, which enables quicker answers and more efficient medical care.

6. AI FOR EARLY DISEASE DETECTION AND PREVENTION

6.1 The Use Of AI In Early Disease Detection And Risk Assessment

Through the examination of massive patient records and the identification of minute patterns and irregularities that may point to the presence of a disease, artificial intelligence plays a significant part in the early illness recognition process. In order to learn from a wide variety of datasets, AI systems can make use of machine learning methods. Medical records, imaging studies, and data from smart devices are all included in this system, which is designed to uncover potentially dangerous elements and early warning indicators.

6.2 The Application Of AI In Analyzing Patient Data, Genetic Information, And Biomarkers

AI is able to analyze genetic data and identify genetic variants that are associated with an increased likelihood of getting a specific illness. A personalized risk assessment score may be possible with the use of AI medical diagnosis systems that combine genetic data with factors affecting lifestyle, environmental impacts, and medical history. It is because of this that people are able to make educated decisions regarding their health and to take preventative steps. Artificial intelligence may also analyze biomarkers, including imaging and blood test results, to find disease-related early warning signs that aren't always obvious to the naked eye.

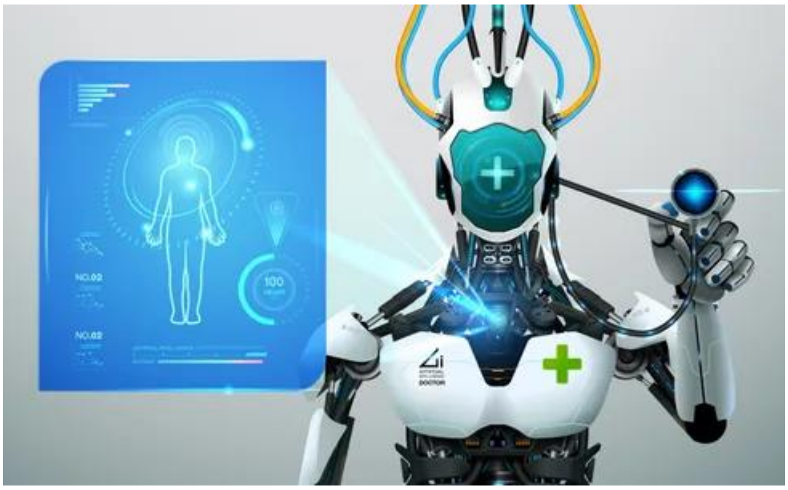
6.3 The Potential For AI To Assist In Personalized Medicine And Preventive Care

There is a significant possibility that AI will advance preventive and individualized medical care. The use of large datasets and machine learning algorithms could pave the way for AI to help personalize healthcare solutions for patients according to their risk assessments and distinct traits. By analyzing a person's genetic composition, medical history, and lifestyle habits, AI-powered systems may one day provide personalized alternatives for illness prevention and treatment. By implementing this technique, we may enhance patient engagement and motivate patients to take an active role in their own health.

7. AI-ASSISTED DIAGNOSIS SUPPORT SYSTEMS

7.1 The Development Of AI-Assisted Diagnosis Support Systems For Healthcare Professionals

The creation of AI-assisted diagnostic aid systems has been propelled in recent years by advancements in machine learning, natural language processing, and big data analytics. These systems have access to a plethora of patient data and medical information because they are built to integrate with electronic health records and clinical databases.



7.2 AI Can Assist In Differential Diagnosis And Treatment Decision-Making

Performing a differential diagnosis, which comprises identifying the most probable cause of a patient's symptoms, may be a difficult and time-consuming process [26]. Machine learning algorithms are utilized by AI medical diagnosis help systems to examine patient data and provide proposed diagnoses in light of patterns and newly discovered scientific facts. Artificial intelligence (AI) could help doctors narrow down their diagnosis options by providing prioritized lists of probable diagnoses, backed up by evidence and probability estimates. In this way, diagnoses might be made more quickly and with more accuracy.

CONCLUSION

Humans and AI collaborate to accomplish a common objective; nonetheless, the accuracy of the underlying mathematical procedure and human components, including trust, are crucial to the success of this undertaking. The complex web of trust between humans and AI can only be understood by adopting a systems view of health care as an evolving sociotechnical system whose constituent parts coordinate their actions. When it comes to health care providers, there are a lot of factors that can affect their level of trust in AI systems. These include organizational policies, culture, the specific tasks they are assigned, similar computational tools, the way they interact with patients and other providers, and internal and external environmental factors. In the medical field, the deployment of AI poses serious challenges. Practitioners are only held accountable when they deviate from the conventional care strategy for a specific health concern, according to current practice. This is true regardless of the patient's health outcome. Notably, doctors may face consequences if they adhere to AI recommendations that deviate from standard care and negatively affect patients' health results.It is anticipated that clinicians who employ AI systems will utilize them to supplement human decision-making rather than to completely replace it. Since humans are still the ones who make the final decisions, this view holds that doctors should still be held accountable for any mistakes made in patient care.

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