(REVIEW ARTICLE)

Horizon of Healthcare: AI's Evolutionary Journey and Future Implications

Shifan Khanday *, Azza shaloob, Fathima maryam muzammil, Hafsah shehzad, Sadia rounak Shriya and Saima khan

Medical College for Girls, Dubai.

Abstract

This meta-analysis offers a comprehensive review of the literature surrounding the integration of Artificial Intelligence (AI) in healthcare. Drawing upon an extensive array of scholarly articles, research papers, and industry reports, this study synthesizes the current state of knowledge regarding AI's applications, challenges, and future directions within the healthcare sector. The analysis encompasses various dimensions of AI implementation, including diagnostic assistance, treatment optimization, patient management, and administrative streamlining. Additionally, it examines the methodological approaches employed in AI healthcare research, assessing the efficacy and reliability of AI-driven interventions across diverse medical domains. Furthermore, this meta-analysis explores the ethical, legal, and social implications associated with AI adoption in healthcare, shedding light on issues of data privacy, algorithmic bias, and patient autonomy. Through a systematic examination of existing literature, this study elucidates key trends, knowledge gaps, and emerging research directions in the evolving intersection of AI and healthcare, providing valuable insights for policymakers, practitioners, and researchers alike.

Keywords: Artificial Intelligence (AI); Healthcare; Literature Review; Meta-Analysis

1. Introduction

The integration of Artificial Intelligence (AI) into healthcare systems has heralded a new era of innovation, promising transformative solutions to age-old challenges and unprecedented advancements in patient care. With the rapid evolution of AI technologies, healthcare professionals and researchers are exploring novel applications across various domains, ranging from diagnostics and treatment planning to administrative tasks and patient management. However, alongside the immense potential benefits, the adoption of AI in healthcare brings forth a myriad of complex issues and considerations. This article presents a comprehensive exploration of the current landscape of AI in healthcare, synthesizing existing literature to elucidate key applications, challenges, and future directions. Through a meta-analysis of scholarly works, research papers, and industry reports, we delve into the multifaceted dimensions of AI implementation, examining its impact on healthcare delivery, clinical decision-making, and patient outcomes. Furthermore, we scrutinize the ethical, legal, and social implications inherent in the use of AI within healthcare settings, addressing concerns such as data privacy, algorithmic bias, and patient autonomy. By critically assessing the state of knowledge surrounding AI in healthcare, this study aims to provide valuable insights for policymakers, healthcare practitioners, and researchers navigating the dynamic intersection of AI and healthcare delivery.

Method: For the literature search, a systematic approach was employed to identify relevant studies pertaining to the utilization of Artificial Intelligence (AI) in healthcare. Databases such as PubMed, Google Scholar, IEEE Xplore, and others were searched using a set of predetermined keywords related to AI and healthcare. Inclusion criteria were established to select articles based on relevance to the topic, publication date, study design, and language. Articles that did not meet these criteria were excluded from the review. Following the search, screening of the search results was

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* Corresponding author: Shifan Khanday.

conducted by reviewing titles and abstracts to identify potentially relevant articles. Selected articles underwent a full-text review to determine their suitability for inclusion in the review based on their relevance to the topic of AI in healthcare.

Subsequently, data extraction was carried out from the selected articles, focusing on key aspects such as study objectives, methodology employed, AI techniques utilized, healthcare applications targeted, findings reported, and any limitations acknowledged by the authors. Quality assessment of the included studies was conducted using established tools such as the Cochrane Collaboration's tool for assessing risk of bias or the Newcastle-Ottawa Scale for observational studies. This step ensured the rigor and reliability of the evidence synthesized in the review.

Following data extraction and quality assessment, a synthesis of the findings from the included articles was performed. This involved summarizing key themes, trends, and gaps identified in the literature related to AI in healthcare. By systematically analyzing and synthesizing the evidence, this review aimed to provide a comprehensive overview of the current state of knowledge regarding the applications, challenges, and future directions of AI in healthcare

2. Results

2.1. Artificial Intelligence in Health Care: Current Applications and Issues - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7606883/

2.1.1. Issues of utilizing health care data

- -health care data typically include personal identification information such as personal code, number, text, voice, sound, and image. To create a data-driven AI medical device, a large amount of these data carrying sensitive personal information are required, but obtaining such sensitive information may lead to legal issues regarding personal privacy
- -However, cloud-assisted AI devices can give rise to serious security concerns to the private health care data.
- -In the U.S., the Health Insurance Portability and Accountability Act (HIPAA) established in 1996 has given individuals the data rights for medical information copies, and the Blue Button system has been established to allow individuals to diversify the use of data through viewing their own personal health records online.
- -Health Information Technology for Economic and Clinical Health Act (HITECH Act) in 2009, an electronic health record has been developed and promoted to increase the interoperability of medical information between hospitals
- -Centers for Medicare & Medicaid has launched the MyHealthEData and Blue Button 2.0 services in 2018 to enable patients to access and control their medical records and other health data
- -In Europe, through the General Data Protection Regulation established in 2016, the basic individual rights for personal information have been reinforced by mandating the EU members to protect personal information in accordance with the six data protection principles
- -However, despite these efforts from many countries, no country has been able to systematically resolve the privacy issues regarding health care data.

2.1.2. Regulatory affairs and policies for new devices

- -Most AI-based medical devices exist in the form of software, and they are generally new devices different from the traditional devices in terms of regulatory affairs.
- -recently developed a Software Precertification Program, which enables faster marketing of Software as a Medical Device (SaMD)
- -Japan planning to create comprehensive rules governing the use of AI in medical devices to minimize the existing AI medical device–related disputes and prevent the resulting R&D hinderances
- -in Korea, the "Approval and Review Guidelines for Big Data and AI-based Medical Devices" and "Review Guidelines for Clinical Effectiveness of AI-based Medical Devices" were announced in 2017, making them some of the first AI-related approval guidelines in the world

2.1.3. Safety and liability issues

- -the federal government is promoting verification of the effectiveness and fairness of AI through the evidence-based assessment, and the federal government funding for research is mandated to be allocated based on the transparency, effectiveness, and fairness

- -government is recommending the universities and secondary schools to include topics related to ethics, safety, and privacy in the AI or data science curriculum
- -The present health care system assumes that all responsibility lies in the hands of the medical staff in the event of a medical accident; AI-based medical technology may sometimes cause negative impacts, resulting in medical accidents. In such cases, liability issues would arise, it is highly likely that the medical institution or physicians who ultimately introduced the AI-based medical technology would be responsible for the case.

2.1.4. Balanced application with existing health care systems

- -the performance of AI devices should be periodically checked even after the clinical application to prevent any unexpected performance degradation or malfunction.
- -necessary to implement the interaction and interface technologies that can enable the medical staff to apply AI technology to the medical field in a natural way even if they do not directly understand the technical aspects of the AI devices

2.2. Revolutionizing healthcare: the role of artificial intelligence in clinical practice - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10517477/

- -This review article provides a comprehensive and up-to-date overview of the current state of AI in clinical practice, including its potential applications in disease diagnosis, treatment recommendations, and patient engagement. It also discusses the associated challenges, covering ethical and legal considerations and the need for human expertise.
- -analyzed the use of AI in the healthcare system with a comprehensive review of relevant indexed literature, such as PubMed/Medline, Scopus, and EMBASE

2.2.1. AI assistance in diagnostics

- -AI can revolutionize different aspects of health care, including diagnosis.
- -ML is an area of AI that uses data as an input resource in which the accuracy is highly dependent on the quantity as well as the quality of the input data that can combat some of the challenges and complexity of diagnosis; can assist in decision-making, manage workflow, and automate tasks in a timely and cost-effective manner.
- -Convolutional Neural Networks (CNN) and data mining techniques that help identify data patterns
- -study was published in the UK where authors input a large dataset of mammograms into an AI system for breast cancer diagnosis: absolute reduction in false positives and false negatives by 5.7% and 9.4%
- -Another study was conducted in South Korea, where authors compared AI diagnoses of breast cancer versus radiologists: 90% vs. 78%, respectively.
- -AI using CNN accurately diagnosed melanoma cases compared to dermatologists and recommended treatment options
- -a study was done on a dataset of 625 cases to diagnose acute appendicitis early to predict the need for appendix surgery using various ML techniques: random forest algorithm achieved the highest performance, accurately predicting appendicitis in 83.75% of cases, with a precision of 84.11%, sensitivity of 81.08%, and specificity of 81.01%.
- -In the future, AI technology could be used to support medical decisions by providing clinicians with real-time assistance and insights.
- -Several ML systems were developed to detect, identify, and quantify microorganisms, diagnose and classify diseases, and predict clinical outcomes.
- -For malaria, Taesik et al. found that using ML algorithms combined with digital in-line holographic microscopy (DIHM) effectively detected malaria-infected red blood cells without staining. This AI technology is rapid, sensitive, and cost-effective in diagnosing malaria
- -AI in clinical microbiology laboratories can assist in choosing appropriate antibiotic treatment regimens
- -in the emergency department (ED): AI algorithms can analyze patient data to assist with triaging patients based on urgency; this helps prioritize high-risk cases, reducing waiting times and improving patient flow

2.2.2. AI assistance in treatment

Precision medicine and clinical decision support

- -Personalized treatment represents a pioneering field that demonstrates the potential of precision medicine on a large scale

- -A study conducted by Huang et al. where authors utilized patients' gene expression data for training a support ML, successfully predicted the response to chemotherapy: achieving a prediction accuracy of over 80% across multiple drugs
- -study performed by Sheu et al., the authors aimed to predict the response to different classes of antidepressants using electronic health records (EHR) of 17,556 patients and AI: that antidepressant response could be accurately predicted using real-world EHR data with AI modeling, suggesting the potential for developing clinical decision support systems for more effective treatment selection.

2.2.3. Dose optimization and therapeutic drug monitoring

- -In a study that aimed to develop an AI-based prediction model for prothrombin time international normalized ratio (PT/INR) and a decision support system for warfarin maintenance dose optimization
- -Therapeutic drug monitoring (TDM) is a process used to optimize drug dosing in individual patients. It is predominantly utilized for drugs with a narrow therapeutic index to avoid both underdosing insufficiently medicating as well as toxic levels.
- -AI in TDM is using ML algorithms to predict drug-drug interactions
- -AI in TDM using predictive analytics to identify patients at high risk of developing adverse drug reactions.

2.2.4. AI assistance in population health management

Predictive analytics and risk assessment

- -By analyzing data such as medical history, demographics, and lifestyle factors, predictive models can identify patients at higher risk of developing these conditions and target interventions to prevent or treat them
- -can help reduce healthcare costs and improve patient outcomes which is the reason behind launching new companies such as "Reveal ®"
- -predictive analytics plays an increasingly important role in population health. Using ML algorithms and other technologies, healthcare organizations can develop predictive models that identify patients at risk for chronic disease or readmission to the hospital

2.2.5. AI in drug information and consultation

- -AI enables quick and comprehensive retrieval of drug-related information from different resources through its ability to analyze the current medical literature, drug databases, and clinical guidelines to provide accurate and evidence-based decisions for healthcare providers
- AI-powered patient care
- AI virtual healthcare assistance
- -Virtual assistants can help patients with tasks such as identifying the underlying problem based on the patient's symptoms, providing medical advice, reminding patients to take their medications, scheduling doctor appointments, and monitoring vital signs

2.2.6. AI mental health support

- -Web-based or Internet-based cognitive-behavioral therapy (CBT) as a psychotherapeutic intervention
- -mental health digital app called Woebot in patients with substance use disorders: with improved substance use, cravings, depression, and anxiety
- -One of the main limitations is the risk of bias in the data and algorithms used in AI-powered diagnosis.(adverse populations,complexity of mental health conditions, lack of empathy)

2.2.7. AI in enhancing patient education and mitigating healthcare provider burnout

- -Researchers found that ChatGPT, an AI Chatbot founded by OpenAI, can help patients with diabetes understand their diagnosis and treatment options, monitor their symptoms and adherence, provide feedback and encouragement, and answer their question
- Are individuals more inclined towards AI than human healthcare providers
- -people's trust and acceptance of AI may vary depending on their age, gender, education level, cultural background, and previous experience with technology

2.3. A Review of the Role of Artificial Intelligence in Healthcare - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10301994/

- -The necessity for deploying advanced digital devices has become a requirement to offer augmented customer satisfaction, permitting tracking, checking the health status, and better drug adherence to be achieved
- -Genomics and other technologies, including biometrics, tissue engineering, and the vaccine industry, can improve and transform diagnostics, therapeutics, care delivery, regenerative treatment, and precision medicine models
- describes the definitions of terms related to AI.

-AI aims to reveal its role in healthcare, focusing on the following key aspects (i) medical imaging and diagnostics, (ii) virtual patient care, (iii) medical research and drug discovery, (iv) patient engagement and compliance, (v) rehabilitation, and (vi) other administrative applications

2.4. Role of AI in Healthcare

Medical Imaging and Diagnostic Services

- -AI tools can analyze body imaging modalities to detect abnormalities associated with diseases like breast cancer and pneumonia. They can also analyze speech patterns to predict psychotic occurrences and identify features of neurological diseases like Parkinson's disease.
- -In a recent study, machine learning (ML) models were utilized to predict the onset of diabetes, with a two-class augmented decision tree showing the best performance in predicting different variables associated with diabetes.
- -AI models like the Vision Transformer (ViT) have been employed to classify breast tissues based on ultrasound (US) images, showing superior efficacy compared to conventional convolutional neural networks (CNNs)
- -GANs consist of two neural networks: a generator that synthesizes images resembling real ones and a discriminator that distinguishes between synthetic and real images; GANs offer opportunities to enhance medical education and research by swiftly generating training materials and simulations for student learning
- -medical imaging-guided diagnosis and therapy, is facilitated by a metaverse of "medical technology and AI" (MeTAI)

2.4.1. Virtual Patient Care

- -metaverse systems could utilize augmented reality (AR) glasses so that the users can access live videotapes and audio chats to interact with clinicians in real time.
- -Remote patient monitoring (RPM) is a subset of telehealth by integrating novel IoT methods: contact-based sensors, wearable devices, and telehealth applications

2.4.2. Medical Research and Drug Discovery

-In drug discovery, AI technologies derived from ML, bioinformatics, and cheminformatics models have significantly reduced the time and cost required for new drug discovery.

2.4.3. Patient Engagement and Compliance

-ChatGPT is being integrated into various healthcare apps to automate tasks such as summarization, note writing, and report production, saving time and enhancing efficiency. These apps assist patients in symptom checking, appointment scheduling, medication management, and self-management of chronic diseases, ultimately promoting patient compliance and education in healthcare settings.

2.5. Explainability for artificial intelligence in healthcare: a multidisciplinary perspective - https://scholar.google.ae/scholar?q=ai+in+healthcare+ncbi&hl=en&as_sdt=0&as_vis=1&oi=scholart#d=gs_q abs&t=1708406007075&u=%23p%3DC7HP1TbAJX4J

- -AI's lack of explainability poses challenges, as understanding why AI makes certain predictions is crucial in the medical domain; AI often takes the form of clinical decision support systems (CDSS), aiding clinicians in diagnosis and treatment decisions
- -Explainability refers to the ability of an AI system to explain its predictions, yet the terminology surrounding it is not well-defined. Despite AI's ability to outperform humans in some analytical tasks, its lack of explainability has raised legal and ethical concerns in the medical field.

- -Explainability can help identify whether prediction accuracy is based on meaningful data or on irrelevant factors, such as background noise or metadata. This phenomenon, known as the "Clever Hans" effect, can lead to misleading predictions.
- -Clever Hans phenomena developed by researchers from Mount Sinai Hospital. While the model performed well in distinguishing high-risk patients based on X-ray imaging, its performance dropped significantly when applied outside of Mount Sinai.

2.5.1. The legal perspective

- -informed consent perspective, patients must have a clear understanding of how AI-based decision support systems (CDSS) work and the potential risks involved
- -liability, there is uncertainty about the extent to which healthcare providers must disclose the use of AI in treatment decisions.
- -FDA and MDR are currently rather vaguely requiring explainability, i.e. information for traceability, transparency, and explainability of development of ML/DL models that inform medical treatment.
- -there is a current debate on whether the General Data Protection Regulation (GDPR) in the European Union requires the use of explainable AI in tools working with patient data
- -the question arises, to what extent the patient has to be made aware that treatment decision; Hacker et al. argue that legally it is likely that explainability will be a prerequisite from a contract and tort law perspective where doctors may have to use a certain tool to avoid the threat of a medical malpractice lawsuit

2.5.2. The medical perspective

- -first consideration is what distinguishes AI-based clinical decision support from established diagnostic tools, such as advanced laboratory testing for example?
- -First level explainability allows us to understand how the system arrives at conclusions in general.
- -Second level explainability allows us to identify which features were important for an individual prediction-this will regularly be available for AI based CDSS but not for other diagnostic tests
- -Depending on the clinical use case and the risk attributed to that particular use case, first level explanations might be sufficient, whereas other use cases will regularly require second level explanations to safe-guard patients.
- -Despite all efforts, however, AI systems cannot provide perfect accuracy owing to different sources of error. For one, because of naturally imperfect datasets in medicine
- -Explainability enables the resolution of disagreement between an AI system and human experts, no matter on whose side the error in judgment is situated

2.5.3. The patient perspective

- -the question of whether the use of AI-powered decision aids is compatible with the inherent values of patient-centered care.
- -A key component of patient-centered care is open conversation between the patient and the clinician
- -Explainability can address this issue by providing clinicians and patients with a personalized conversation aid that is based on the patient's individual characteristics and risk factors
- -explainability provides a visual representation or natural language explanation of how different factors contributed to the final risk assessment

2.5.4. Ethical implications

- -At the moment, an ethical consensus has not yet emerged as to whether disclosing the use of an opaque medical AI algorithm should be a mandatory requirement of informed consent.
- -A failure to disclose the use of an opaque AI system may undermine patients' autonomy and negatively impact the doctor-patient relationship, jeopardizing patients' trust, and might violate the compliance with clinical recommendations
- -If the patient were to find out in hindsight that a clinician's recommendation was derived from an opaque AI system, this may lead the patient to not only challenge the recommendation but might also lead to a justified request for explanation—which in the case of an opaque system, the clinician would not be able to provide.
- -opaque AI into medical decision limits patients to express their expectations and preferences;full autonomy only if patient presented with meaningful options
- -explainability is—both from the physician's and patient's point-of-view—an ethical prerequisite for systems supporting critical medical decision making

- -Beneficence urges physicians to maximize patient benefits. When applying AI-based systems, physicians are thus expected to use the tools in a manner that promotes the optimal outcome for the respective patient
- -The optimal outcome for all patients can only be expected with healthcare staff that can make informed decisions when to apply an AI-powered CDSS and how to interpret its results. It is thus hard to imagine how beneficence in the context of medical AI can be fulfilled with any "black box" application.
- -Non-maleficence states that physicians have a fundamental duty not to harm their patients either intentionally or through excessive or inappropriate use of medical means.
- -The principle of justice postulates that people should have equal access to the benefits of medical progress without ethically unjustified discrimination of any particular individuals or social group;for example, Obermeyer et al. reported on a medical AI system discriminating against people of color
- -Explainability can support developers and clinicians to detect and correct such biases—a major potential source for injustice—ideally at the early stage of AI development and validation, e.g. by identification of important features indicating a bias in the model

BENEFITS

2.6. A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities - https://www.sciencedirect.com/science/article/pii/S2444569X2300029X

2.6.1. Benefits to Individuals

AI offers numerous advantages to individuals, encompassing automated decision-making, patient monitoring, including the monitoring of elderly patients, early diagnosis, and process simplification. AI's capability to analyze big data effectively and devise innovative solutions is particularly noteworthy, benefiting healthcare practitioners and patients alike. This technology provides a convenient solution to overcome challenges, as it can generate automatic inferences with minimal or no human intervention. Some studies even suggest that AI can outperform humans in specific medical scenarios, such as radiology, cardiology, and tumor detection. Chronic diseases, which place a considerable burden on the healthcare sector in terms of effort and cost due to frequent patient visits, can be better managed with the integration of health coaching and AI. By reducing the need for unnecessary visits, this model enhances chronic disease management while reducing expenses.

2.6.2. Benefits to Organizations

Organizations harness AI applications and IT tools to reduce costs, detect fraud, enhance performance, and streamline workflows. For example, Murray et al. (2019) highlight the challenge of extracting knowledge automatically from clinical information systems due to limited data normalization and integration. They propose an AI-empowered network (AI-KEN) to address these issues, which automatically generates clinical notes and ensures data normalization and integration from multiple sources. Various studies advocate for the implementation of AI in healthcare to reduce resource consumption and costs. AI can also aid the healthcare sector in detecting fraudulent claims, a significant issue causing substantial financial losses. Researchers recommend hybrid AI solutions combining clustering and classification techniques to identify fraudulent claims effectively.

2.6.3. Benefits to the Sector

The healthcare sector as a whole, comprising hospitals, insurance companies, and government agencies, benefits extensively from AI technologies. By leveraging patient data collected through IT systems, AI supports professional training and contributes to time and resource savings. Extending AI solutions to healthcare offers numerous advantages, including minimizing resource consumption, reducing treatment expenses and time, accelerating diagnosis, and enhancing decision-making processes. Data sharing is crucial in healthcare for individual well-being and scientific research progress. However, accessing medical data faces regulatory and privacy challenges. Solutions like the personal health train (PHT) system and integrating AI into medical education curricula can address these challenges and promote advancements across the entire healthcare sector

2.7. Benefits of Information Technology in Healthcare: Artificial Intelligence, Internet of Things, and Personal Health Records - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10651408/

2.7.1. Clinical Effects

Disease Diagnosis Accuracy

The diagnostic accuracy of AI, compared to healthcare professionals and existing diagnostic methods, is summarized below. AI diagnosis showed superior accuracy in seven out of 12 areas compared to existing methods. When compared to healthcare professionals, AI exhibited higher diagnostic accuracy in six out of ten areas. For instance, a study comparing AI with existing methods for diagnosing coronary artery diseases found the AI-based approach to be more effective .

Diagnostic Efficacy

Assessing the efficacy of diagnostic tests involves utilizing receiver operating characteristic curves and calculating the area under the curve (AUC) based on sensitivity and specificity. Across 18 meta-analysis studies on AI, the diagnostic efficacy was evaluated in 25 areas using the AUC. Results indicated good diagnostic efficacy, with AUC scores ranging from 0.83 to 0.99 ,

Treatment Prediction and Reduction of Side Effects and Medical Errors:

AI application in clinical practice aids in identifying suitable treatment options, reducing side effects and medical errors, cutting costs, and facilitating further integration of research and practice. AI enables the exploration and identification of new genotypes and phenotypes of existing diseases, improving patient care quality. For example, AI has been capable of predicting the onset of acute kidney injury in hospitalized patients 48 hours in advance, enabling timely intervention

2.7.2. Managerial and Socioeconomic Effects

Medical Benefit

Enhanced Data-Driven Decision Making:

Smart data inclusion significantly contributes to improving decision-making quality in healthcare, assisting in identifying decisions, acquiring information, and evaluating possible remedies. AI utilizes patient data for clinical decision-making, hospital data for operational decision-making, and data about patients and hospitals for consumer decision-making.

Improvement in Surgery

AI advancements, including surgical robots, augmented reality (AR), and tele-surgical approaches, enhance surgical precision, predictability, and mentorship. These technologies enable remote surgery, intraoperative guidance, and real-time counseling, ultimately minimizing patient hospital stay and offering newer surgical approaches based on patient history.

Support for Mental Health

AI, through natural language processing (NLP) and sentiment analysis, aids in measuring mental health by deducing emotional meaning from various data sources. NLP models detect suicidal thoughts, forecast suicide risk, and mine psychiatric self-disclosure on social media, enhancing mental health assessment accuracy.

Economic and Social Benefits

Elimination of Expenditures Associated with Post-Treatment Problems

AI facilitates clinical decision-making to ensure tailored interventions and therapies, leading to improved outcomes and elimination of expenditures related to post-treatment issues, a major cost driver in healthcare ecosystems worldwide.

Cost Reduction through Early Diagnostics

AI-enabled devices execute repetitive tasks accurately, facilitating early diagnosis and action, thus reducing physician errors and healthcare costs. AI demonstrates high precision in analyzing mammograms and identifying vertebral fractures, leading to early detection of diseases like breast cancer and osteoporosis.

Cost Minimization with Enhanced Clinical Trials

AI accelerates pharmaceutical development by simulating and analyzing potential treatments, saving costs and lives. Biomarker monitoring frameworks and patient data analysis optimize medication development in clinical trials, resulting in cost savings.

Patient Empowerment

AI empowers individuals to make informed health decisions by analyzing wearable technology data and providing personalized patient profiles. This leads to healthier populations, lower healthcare costs, and improved disease control among chronic patients.

CHALLENGES

2.8. Drawbacks of Artificial Intelligence and Their Potential Solutions in the Healthcare Sector - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9908503/

2.8.1. Data collection concern

The confidentiality of patient records poses challenges to the exchange of health data among institutions, compounded by difficulties in accessing data once algorithms are implemented. Concerns about data security and privacy arise with AI-based systems, especially due to the susceptibility of health records to hacking. Ensuring confidentiality is crucial, as advancements in AI may lead users to unknowingly consent to covert data collection. Assessing data quality is challenging due to the short lifespan of patient data and the inherent disorganization of medical records, leading to unforeseen gaps in datasets used for AI development.

2.8.2. Social and Ethical concerns

Artificial intelligence (AI) is often perceived as a "black box" because understanding how an algorithm reaches a specific conclusion can be challenging. This opacity raises concerns about accountability in the event of system failures, as it may not be clear who is responsible. Doctors may not be held accountable if they were not involved in developing or overseeing the algorithm, while blaming the developer might seem disconnected from the clinical context. The lack of standardized guidelines for the ethical use of AI and machine learning (ML) in healthcare exacerbates these issues. The absence of universal guidelines has sparked debates about the appropriate extent of AI utilization in healthcare settings.

2.8.3. Clinical implementation

The primary obstacle hindering the successful deployment of AI-based medications in healthcare is the lack of empirical data validating their effectiveness through planned clinical trials. Most of the research on AI's application has been conducted in business settings, leaving a gap in understanding its impact on patient outcomes. Furthermore, the majority of healthcare AI research has been conducted outside of clinical environments, making it challenging to generalize results. Traditional randomized controlled studies, considered the gold standard in medicine, struggle to demonstrate the benefits of AI in healthcare due to these limitations. As a result, businesses are hesitant to implement AI-based solutions due to the absence of practical data and varying research quality. Integration of AI into medical processes for more efficient use has been hindered by concerns about the usability of information systems and the potential for AI-based treatments to slow down clinicians during patient care. Additionally, the investment of time and resources required to train medical professionals in effectively utilizing AI technology adds to the hesitancy surrounding its implementation.

2.9. Real-world application, challenges and implication of artificial intelligence in healthcare: an essay - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9557803/

- Data privacy and cybersecurity: AI-based systems collecting and sharing confidential patient data must adhere to medical ethics and laws to mitigate privacy risks. Unauthorized access to patient data and potential misdiagnoses due to falsified data are significant concerns.

- Reliability and safety: Errors in AI systems can lead to incorrect task outcomes with serious consequences, such as inappropriate medical recommendations, highlighting the importance of reliability and safety in AI applications.
- Accountability of technology use: Questions arise regarding responsibility in adverse patient outcomes resulting from AI technology, posing technical, managerial, and ethical challenges that need to be addressed.
- Potential loss of support system and autonomy: While AI health apps can empower individuals to manage their symptoms independently, there are concerns about reduced reliance on healthcare workers, potential isolation, and limitations on patient autonomy in treatment decisions.
- Challenges in generalization to new populations: Generalizing AI systems to new populations remains challenging, as reliable clinical applications for various medical data types are still being developed.
- Technological challenges: AI model development lacks transparency, and errors in design can lead to incorrect results. Additionally, AI systems struggle to handle unstructured medical imaging data and lack standardized data inputs, posing challenges in healthcare application.
- Organizational and managerial challenges: Challenges include data exchange, workforce retention, and potential loss of skilled healthcare providers due to AI implementation.
- Malicious use: Despite its potential benefits, AI is susceptible to malicious use, including covert monitoring and analysis of individuals' behaviors for unauthorized purposes.

2.10. Challenges to implementing artificial intelligence in healthcare: a qualitative interview study with healthcare leaders in Sweden - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9250210/

Healthcare leaders have identified various implementation challenges related to integrating AI within and beyond healthcare organizations. These challenges encompass external factors, internal capacity for strategic change management, and the transformation of healthcare professions and practices. Our research underscores the importance of viewing the implementation of AI systems in healthcare as an evolving learning process across all organizational levels. This approach necessitates adopting a more nuanced systems thinking within the healthcare system. It is critical to actively engage and collaborate with stakeholders and users within the regional healthcare system, as well as external actors, to effectively develop and apply system thinking principles in AI implementation.

2.11. Sources of bias in artificial intelligence that perpetuate healthcare disparities—A global review - https://journals.plos.org/digitalhealth/article?id=10.1371/journal.pdig.0000022&utm

This study highlights significant disparities in the data sources used to develop clinical AI models, as well as in the representation of specialties and authors' characteristics such as gender, nationality, and expertise. It was found that the top databases and author nationalities were primarily affiliated with high-income countries, particularly the U.S. and China. Radiology was notably overrepresented among specialties, possibly due to facilitated access to image data. Additionally, a significant portion of authors contributing to clinical AI manuscripts had non-clinical backgrounds and were predominantly male.

Most AI models are trained using data from the U.S. and China, reflecting the advanced technological infrastructure and data availability in these regions. While this overrepresentation poses risks of bias and disparity, it underscores the importance of understanding when and why these models remain beneficial, especially in data-poor and demographically diverse regions.

Model pre-training offers a mechanism for applying AI developed in data-rich areas to data-poor regions. However, biases inherent in these models could exacerbate healthcare inequality if not properly addressed. External validation is crucial for ensuring model accuracy and applicability to diverse populations, particularly within the same country.

The complexity of generalizability underscores the need for ongoing assessment and monitoring of AI models' performance in different clinical contexts. By understanding the circumstances in which AI-based models provide valuable insights and identifying settings where they may fall short, we can enhance their utility in clinical practice.

3. Application

3.1. Application of machine and deep learning algorithms in intelligent clinical decision support systems in healthcare - https://scholar.google.ae/scholar?q=ai+in+healthcare+ncbi&hl=en&as_sdt=0&as_vis=1&oi=scholart#d=gs_q abs&t=1708405939101&u=%23p%3DbTkzhOE1ZFUJ

In response to the need to risk stratify patients, appropriately cultivated and curated data can assist decision-makers in stratifying preoperative patients into risk categories, as well as categorizing the severity of ailments and health for non-operative patients admitted to hospitals.

Previous overt, traditional vital signs and laboratory values that are used to signal alarms for an acutely decompensating patient may be replaced by continuously monitoring and updating AI tools that can pick up early imperceptible patterns predicting subtle health deterioration.AI may help overcome challenges with multiple outcome optimization limitations or sequential decision-making protocols that limit individualized patient care.

Despite these tremendously helpful advancements, the data sets that AI models train on and develop have the potential for misapplication and thereby create concerns for application bias. Subsequently, the mechanisms governing this disruptive innovation must be understood by clinical decision-makers to prevent unnecessary harm.

Artificial intelligence (AI) methods, in particular machine learning (ML), reinforcement learning, and deep learning, are particularly well-suited to deal with both the data type and looming questions in healthcare. AI can aide physicians in the complex task of risk stratifying patients for interventions, identifying those most at risk of imminent decompensation, and evaluating multiple small outcomes to optimize overall patient outcomes

Integrating physicians into model development and educating physicians in this field will be the next paradigm shift in medical education. For example, the complexity of AI methodologies varies greatly, in turn impacting the ease of physician understanding and interpretation of results. Physicians frequently use decision trees as tools; however, they are effectively tied to the initial tree structure and thus somewhat static.

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3.1.1. Risk stratification

ML models that can risk-stratify patients in preparation for surgery will help clinicians identify high-risk patients and optimize resource use and perioperative decisions. ML and AI can help clinicians, patients, and their families efficiently process all available data to generate informed, evidence-based recommendations and participate in shared decision-making to identify the best course of action.

Most risk-prediction tools are historically built based upon statistical regression models. Examples include the Framingham risk score, QRISK3 (for coronary heart disease, ischemic stroke, and transient ischemic attack), and National Surgical Quality Improvement Program (NSQIP).

Preoperative evaluation clinics focusing on evaluating high-risk patients have shown improvement in 30-day postoperative outcomes. However, identifying these patients is challenging because of the difficulty in timely access to patient data coupled with the lack of robust predictive models.

Incorporating intraoperative data for early detection of complications or clinical aberrations could also prevent inflammatory reactions that exacerbate the injury or high-risk interventions that may lead to iatrogenic injuries.

3.1.2. Patient outcome optimization

ML methods can be valuable tools for optimizing patient care outcomes in a data-driven manner, especially in acute care settings. ML and modern deep-learning techniques typically optimize an objective function (e.g., medication dosage) based on complex and multidimensional data (e.g., patient medical history extracted from EHRs).

ML tools for optimizing care outcomes have been used in various settings, including critical care for optimizing sepsis management , management of chronic conditions , and optimizing surgical outcomes. Optimizing patient outcomes can be based on relatively simple yet efficient tools, such as decision trees in conjunction with the domain expertise to systematically codify accepted understanding of disease models and common treatments for patients.

deep reinforcement learning models are based on well-known concepts such as the Markov decision process (MDP) and Q-learning adapted to neural networks. ecently, reinforcement learning and deep reinforcement learning have been used in several clinical settings, including optimal dosing and choice of medications, optimal timing of interventions, and optimal individual target laboratory values. For example, Nemati et al. used deep reinforcement learning to optimize medication dosing, and Prasad et al.used a reinforcement learning approach to weaning mechanical ventilation in the intensive care unit.

although early interventions (e.g., early antibiotics) may not lead to immediate improvements, they could culminate in the greatest ultimate reward (e.g., higher survival rate).

Patient outcome optimization such as reinforcement learning methods can ultimately provide a tool to help standardise care at health systems of different scales. This could provide a more equitable healthcare system, especially in rural and remote settings.

3.1.3. Early warning of acute decompensation

Vital sign monitoring and associated alarms were one of the earliest methods to detect patient decompensation. They are effective in alerting providers to discrete vital sign abnormalities in real time; however, early or isolated vital sign abnormalities also may fail to signal to providers an impending decompensation.

The Modified Early Warning Score (MEWS), Rothman Index, Sequential Organ Failure Assessment Score (SOFA), and quick SOFA (qSOFA) were developed to incorporate multiple vital sign abnormalities to identify at-risk patients before decompensation occurs

Using AI to effectively create an early-warning score using time series data from the EHR presents many challenges. An ideal score would identify patients before an obvious decompensation. It would have excellent discriminatory ability so that physicians would have confidence implementing appropriate interventions as well as transparency to identify the sources of risk and the reasons for decompensation.

3.1.4. Potential for Bias in ML

broadly, such bias can originate from the data used for model training and testing, as well as the mechanics of the model itself. Bias originating from data can be pernicious; for instance, work by Weber et al. found that simply filtering for "complete" EHRs, a common strategy for managing missing data, introduced a bias toward older patients who were more likely female.

3.1.5. Paradigmatic Shift in Medical Training

Applying advances in biomedical informatics and ML models to patient care will require clinicians to reconsider their educational training and infrastructure.

Understanding principles of normal variants of anatomy and physiology, followed by an examination of pathophysiologic variants, presents students with a model-based rubric in which to incorporate each new wave of information learned through personal experience as well as throughout the medical literature. This paradigm has also permitted physicians to extrapolate previous understanding by logic and experience to novel diagnostic reasoning and therapeutic approaches by extension of previous models.

Humans are not only incapable of this level of exposure or retention, but the magnitude has also created substantial levels of stress-induced mental illness among learners. Fortunately, advances in biomedical informatics point to new approaches that can seamlessly synthesise old and new medical information. These advances will provide the foundation for AI advances to recognize patterns of patient information to help diagnose, treat, and manage patients. This transition will require the development of new knowledge, skills, and attitudes by healthcare workers. Furthermore, it will require a rethinking of the medical school curriculum, in which new data analytics methods are carefully integrated with traditional medical education.

AI capabilities will aide physicians in weighing competing healthcare goals and numerous risks by facilitating multiple outcome optimization of outcomes that are too difficult to recognize and navigate on an individual and isolated basis. Healthcare workers will be expected to comfortably work within this new AI frontier and in turn relate it to their patient

3.2. AI-Assisted Decision-making in Healthcare - https://link.springer.com/article/10.1007/s41649-019-00096-0

AI-assisted data analysis and learning tools have been used widely in research with patient electronic health records (EHRs). These records were previously kept on paper within hospitals but now exist electronically on secure computer servers.

The increasing computational power of hardware and AI algorithms is also enabling the introduction of platforms that can link EHRs with other sources of data, such as biomedical research databases, genome sequencing databanks, pathology laboratories, insurance claims, and pharmacovigilance surveillance systems, as well as data collected from mobile Internet of Things (IoT) devices such as heart rate monitors.

These *Clinical Decision Support Systems* (CDSS) are programmed with rule-based systems, fuzzy logic, artificial neural networks, Bayesian networks, as well as general machine-learning techniques (Wagholikar et al. 2012). CDSS with learning algorithms are currently under development to *assist* clinicians with their decision-making based on prior successful diagnoses, treatment, and prognostication

The App may therefore assist clinicians in better communicating their concerns about the patients' chance of survival and exposure to unnecessary, highly burdensome treatments.

 use AI-assisted CDSS to provide diagnoses to patients and predict treatment outcomes based on relevant clinical data, such as medical and social history, socio-demographics, diagnostic tests, and genome sequences, that are recorded into patient's EHR and fed back into the CDSS for incremental machine learning. AI-assisted CDSS is used to conduct research on patient populations to calculate the risks of non-compliance to prescribed management plans for individual patients. AI-assisted CDSS is used to generate knowledge bases to improve system-wide efficiencies and patient outcomes in learning healthcare systems.

3.3. Evaluation framework to guide implementation of AI systems into healthcare settings- https://scholar.google.ae/scholar?q=ai+in+healthcare+ncbi&hl=en&as_sdt=0&as_vis=1&oi=scholart#d=gs_q abs&t=1708406250160&u=%23p%3D-7gNNjbvSnkJ

Using and integrating AI systems in clinical settings can be potentially expensive and disruptive, thus necessitating strong justification for their deployment. As a result of, it is sometimes difficult to have confidence in the generalizability of the AI systems and adopters may face unnecessary roadblocks on the path to an effective healthcare response. Therefore, a rigorous evaluation that assesses AI systems early and at various stages of their clinical deployment, is crucial.

Currently available evaluation frameworks for AI systems in healthcare generally focus on reporting and regulatory aspects. This is helpful when you have AI systems deployed in healthcare services and integrated with clinical workflow.

Currently available evaluation and reporting frameworks fall short in adequately assessing the functional, utility and ethical aspects of the models despite growing evidence about the limited adaptability of AI systems in healthcare. The absence especially of an assessment of the ethical dimensions such as privacy, non-maleficence and explainability in the available frameworks indicates their inadequacy in providing an inclusive and translational evaluation.

TEHAI includes three main components capability, adoption and utility to assess various AI systems.

3.3.1. Capability

This component assesses the intrinsic technical capability of the AI system to perform its expected purpose, by reviewing key aspects as to how the AI system was developed. Unless the model has been trained and tested appropriately, it is unlikely the system will be useful in healthcare environments.

Objective: This subcomponent is scored on a scale of how well the objective is articulated, that is, the problem the AI addresses, why the study is being conducted and how it adds to the body of knowledge in the domain are clearly articulated.

Dataset source and integrity: This subcomponent evaluates the source of the data and the integrity of datasets used for training and testing the AI system including an appraisal of the representation and coverage of the target population in the data, and the consistency and reproducibility of the data collection process.

Internal validity: An internally valid model will be able to predict health outcomes reliably and accurately within a predefined set of data resources that were used wholly or partially when training the model

External validity : To evaluate external validity, we investigate whether the external data used to assess model performance came from substantially distinct external sources that did not contribute any data towards model training

Performance metrics : Performance metrics refer to mathematical formulas that are used for assessing how well an AI model predicts clinical or other health outcomes from the data. This subcomponent examines whether appropriate performance measures relevant to the given task had been selected for the presentation of the study results.

3.3.2. -Utility

This component evaluates the usability of the AI system across different dimensions including the contextual relevance, and safety and ethical considerations regarding eventual deployment into clinical practice. It also assesses the efficiency of the system (achieving maximum productivity while working in a competent manner) as evaluated through the quality, adoption and alignment measures. Utility as measured through these dimensions assesses the applicability of the AI system for the particular use case and the domain in general.

- It is critical that AI models being deployed in healthcare, especially in clinical environments, are assessed for their safety and quality
- Transparency: This subcomponent assesses the extent to which model functionality and architecture is described in the study and the extent to which decisions reached by the algorithm are understandable
- Privacy This subcomponent refers to personal privacy, data protection and security. This subcomponent is ethically relevant to the concept of autonomy/self-determination, including the right to control access to and use of personal information, and the consent processes used to authorise data uses.
- Non-maleficence This subcomponent refers to the identification of actual and potential harms, beyond patient safety, caused by the AI and any actions taken to avoid foreseeable or unintentional harms.

3.3.3. -Adoption

There have been issues with the adoption and integration of AI systems in healthcare delivery even with those that have demonstrated their efficacy, although in in-silico or controlled environments. Therefore, it is important to assess the translational value of current AI systems. This component appraises this by evaluating key elements that demonstrate the adoption of the model in real life settings.

Use in a healthcare setting: As many AI systems have been developed in controlled environments or in silico there is a need to assess for evidence of use in real world environments and integration of new AI models with existing health service information systems.

Technical integration: This subcomponent evaluates how well the models integrate with existing clinical/administrative workflows outside of the development setting, and their performance in such situations.

Number of services: In this subcomponent, we review reporting quantitative assessment of wider use. This subcomponent is scored according to how well the use of the system across multiple healthcare organisations and/or multiple types of healthcare environments is described.

Evaluating AI models' predeployment and postdeployment along the AI-life cycle can identify potential concerns and issues with the model, avoiding harmful effects on patients' outcomes and clinical decision making.

One of the major limitations with many existing reporting or evaluation frameworks is their narrow focus. Some focus on reporting of clinical trials evaluating AI interventions on a specific medical domain or compare a particular type of AI model to human clinicians limiting the generalisability of such frameworks.

Health services may also need to evaluate AI applications for safety, quality and efficacy, before their adoption and integration.

3.4. The potential of ChatGPT to transform healthcare and address ethical challenges in artificial intelligence-driven medicine - https://scholar.google.ae/scholar?q=ai+in+healthcare+ncbi&hl=en&as_sdt=0&as_vis=1&oi=scholart#d=gs_q abs&t=1708406432094&u=%23p%3D-OR4BKlaZ94J

A previous study of deep-learning models based on long short-term memory (LSTM) for screening Parkinson's disease was an excellent example of how artificial intelligence (AI) can improve the accuracy and efficiency of disease diagnoses.[3] The authors demonstrated that LSTM neural networks trained in sequential diagnostic codes from electronic health records provided more-accurate and sensitive diagnoses of Parkinson's disease compared with using traditional machine-learning methods.

Big-data repositories can be used in the development of AI-powered clinical decision support systems (CDSSs) to improve diagnostic accuracy and support medical professionals, including in areas outside their specialties.

ChatGPT can process vast amounts of medical data, including electronic health records, to aid medical professionals in making informed decisions, particularly when faced with complex or rare diseases that fall outside their areas of expertise. ChatGPT can also contribute to the development of more-accurate screening algorithms.

3.4.1. Ethical challenges of chatGPT

Data privacy: Strict data protection protocols and adherence to privacy regulations are vital when utilising AI-based systems such as ChatGPT in healthcare.

Judgement errors: It is crucial to continuously improve the quality of training data sets and implement human–AI collaboration, such that medical professionals are assisted by AI while maintaining the final decision-making authority.

Bias and fairness: It is crucial to develop strategies that identify and mitigate biases in AI models such as ChatGPT to ensure equitable healthcare outcomes.

Accountability: Clear guidelines must be established to determine who is responsible for errors and adverse outcomes related to AI-assisted healthcare decisions.

3.4.2. Use of chatGPT

The physician interacts with ChatGPT by providing a detailed description of the symptoms, medical history, and any available test results of the patient. The assistance of ChatGPT provides the physician with different perspectives and suggestions that they might not have considered initially. The physician can review the recommendations provided by ChatGPT, evaluate them based on their medical expertise, and then make an informed decision about the next steps in diagnosis and treatment.

ChatGPT acts as a supportive tool, augmenting the knowledge of and decision-making process used by the physician. It is important to note that the final decision rests with the physician, who would combine their clinical expertise with the insights provided by ChatGPT. The collaboration of the expertise from AI and the physician can contribute to improved diagnostic accuracy in this context, especially for complex or rare cases.

Addressing hallucination when applying ChatGPT to healthcare-related AI is a significant challenge. It requires the model to be carefully trained and fine-tuned to ensure that it provides reliable and accurate information. Medical professionals need to critically evaluate the outputs from ChatGPT and exercise their judgement to ensure that the generated information is accurate and appropriate. Clinicians solely relying on AI algorithms without fully understanding the underlying principles or engaging in independent clinical reasoning may both compromise patient safety and inhibit the development of their own medical knowledge.

It is important to establish appropriate guidelines and training programs that emphasise the responsible use of AI tools such as ChatGPT in order to address the dependency issue.

Regular evaluation of AI-based systems, continuous professional development, and encouraging interdisciplinary collaboration can help to mitigate the risk of overreliance on AI algorithms and ensure that healthcare professionals maintain their clinical skills and expertise.

4. Conclusion

In conclusion, this meta-analysis delves into the multifaceted landscape of integrating Artificial Intelligence (AI) into healthcare, offering a comprehensive synthesis of current research findings, challenges, and future prospects. Through an exhaustive review of scholarly works and industry reports, the study explores the breadth of AI applications in healthcare, spanning from diagnostic support to administrative streamlining. Methodological approaches and the efficacy of AI-driven interventions are scrutinized across various medical domains, while ethical, legal, and social implications are carefully considered, emphasizing the importance of addressing issues such as data privacy and algorithmic bias. By systematically analyzing existing literature, this study illuminates crucial trends, identifies knowledge gaps, and points towards emerging research directions at the nexus of AI and healthcare. These insights serve as invaluable resources for policymakers, practitioners, and researchers seeking to navigate and harness the transformative potential of AI in improving healthcare delivery and patient outcomes.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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