Impact of artificial intelligence on medical diagnosis and treatment: a systematic review

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Abstract

Introduction: Artificial intelligence (AI) has emerged as a tool of growing relevance in modern healthcare. Nevertheless, persistent clinical challenges such as diagnostic errors, treatment delays, and variability in medical decision-making continue to affect patient outcomes and healthcare costs. In this context, AI is considered a potential strategy to optimize clinical processes and support medical decisions.

Methods: A protocol was registered in PROSPERO (ID: CRD42024000000). Systematic searches were conducted in PubMed, IEEE Xplore, Scopus, and Web of Science. Primary studies, clinical trials, and systematic reviews evaluating AI applications in diagnosis and treatment were included. Predefined inclusion and exclusion criteria were applied, and methodological quality was assessed using the Jadad scale and the STROBE checklist.

Results: Fifteen studies covering multiple medical specialties were included. Overall findings suggest that AI tools may improve diagnostic accuracy, reduce clinical analysis time, and contribute to therapeutic personalization. Methodological assessment indicated a low to moderate risk of bias in most studies.

Discussion: The analyzed evidence indicates that AI holds significant potential as a clinical support tool, particularly in medical imaging and decision-support systems. However, its implementation faces challenges related to external validation, regulation, ethics, and professional adoption.

Conclusion: Artificial intelligence represents a promising technology for strengthening diagnostic precision and treatment optimization in health-

care. Nevertheless, further research with larger sample sizes and more robust methodological designs is required to consolidate its safe and effective integration into clinical practice.

Keywords: Artificial Intelligence; Healthcare; Diagnosis; Treatment; Systematic Review; Clinical Decision Support.

Introduction

Artificial intelligence (AI) has emerged as a transformative force across multiple fields, and healthcare is no exception (1). From the analysis of large volumes of data to the automation of complex processes, AI offers powerful tools to improve the quality of healthcare and optimize patient outcomes (2,3). The need for more precise, personalized, and efficient healthcare is increasingly evident, particularly in a global context where the demand for health services continues to grow (4).

Traditional diagnostic and treatment methods, although fundamental, present inherent limitations that may affect the quality of care (5). AI has the potential to overcome many of these limitations by providing data-driven solutions that can lead to more accurate diagnoses and more effective treatments (6). However, the integration of AI into healthcare poses significant challenges, including ethical, technical, and regulatory issues that must be addressed to ensure its safe and effective implementation (7).

This systematic review aims to evaluate the impact of AI on the accuracy of medical diagnoses, examining how these technologies have improved the detection of diseases and medical conditions. Additionally, it seeks to analyze their influence on therapeutic processes in healthcare through a critical evaluation of the existing literature, in order to provide a comprehensive overview of the advances, benefits, and challenges associated with their application in the healthcare field (8).

Methodology

Inclusion and Exclusion Criteria

To ensure the relevance and quality of the studies included in the review, the following criteria were established:

Inclusion criteria:

- **Types of studies:** Primary studies, clinical trials, cohort studies, case-control studies, and systematic reviews providing direct evidence on the application of AI in healthcare were included (13).
- **Population:** Patients from various medical specialties who received AI-assisted diagnosis or treatment were considered. Both general

and specific populations (e.g., patients with cancer, diabetes, or cardiovascular diseases) were included (14).

- **Interventions:** Applications of AI used for diagnosis, treatment, or personalization of healthcare. These included machine learning algorithms, deep neural networks, and clinical decision support systems (15).
- **Comparisons:** Studies comparing the effectiveness of AI with traditional diagnostic and treatment methods were included. Evaluations of accuracy, effectiveness, and outcomes between AI-based technologies and conventional approaches were considered (16).
- **Outcomes:** Measures of diagnostic accuracy, treatment effectiveness, impact on clinical outcomes, and personalization of care. Both quantitative outcomes (e.g., accuracy rates, symptom reduction) and qualitative outcomes (e.g., patient satisfaction) were assessed (17).

Exclusion criteria:

- **Irrelevant studies:** Studies not focused on AI applications in medical diagnosis or treatment, or lacking relevant data on the effectiveness of these interventions, were excluded (18).
- **Language:** Studies not available in English or Spanish were excluded due to limitations in interpretation and analysis (19).
- **Insufficient data:** Studies with incomplete or unclear data that did not allow proper evaluation of outcomes were excluded (20).

Search Strategy

The search strategy was designed to be comprehensive and systematic to identify the largest possible number of relevant studies.

- **Databases used:** PubMed, IEEE Xplore, Scopus, and Web of Science (21–24).
- **Search terms:** Combinations of relevant terms with Boolean operators were used to refine results:
  - **General terms:** “artificial intelligence,” “healthcare,” “diagnosis,” “treatment,” “systematic review” (25).
  - **Specific terms**: “machine learning,” “deep learning,” “predictive analytics,” “clinical decision support,” “personalized medicine” (26).

Applied filters:

- **Publication date:** Studies published from 2010 to the date of the search were included (27).
- **Study type:** Primary studies, clinical trials, and systematic reviews (28).
- **Language:** English and Spanish (29).

Search process:

- **Initial search:** A broad search was conducted using the defined terms (30).
- **Title and abstract screening:** Studies were assessed for relevance (31).
- **Full-text evaluation:** Selected studies were reviewed in depth to verify compliance with inclusion and exclusion criteria (32).
- **Data extraction:** Relevant data were extracted using a standardized extraction form (33).

Study Selection Process

The study selection process is a critical stage in a systematic review, ensuring that included studies are relevant and of high quality. This process was conducted in several phases to guarantee thoroughness and accuracy in identifying pertinent studies.

- **Initial screening:** Titles and abstracts of studies identified through the literature search were reviewed to exclude those not meeting inclusion criteria. Priority was given to studies addressing applications of artificial intelligence in medical diagnosis and treatment. This phase allowed the removal of irrelevant studies and focused the analysis on potentially eligible ones. The screening was performed by two independent reviewers to minimize selection bias and reduce the likelihood of omitting relevant studies.
- **Full-text review**: Following the initial screening, a detailed evaluation of full-text articles was conducted. This stage involved comprehensive reading of studies that passed the first phase. Reviewers analyzed methods, results, and discussions to determine relevance and quality. Particular attention was given to study objectives, design, population, data collection methods, and statistical analyses. This process ensured that only studies meeting predefined inclusion criteria were considered. Full-text review allowed a deeper assessment of the quality and applicability of each study.

Data Extraction: Use of a Standardized Template

Data extraction was performed using a standardized template designed to systematically and consistently collect relevant information. This included variables such as study objectives, design, population characteristics, interventions, comparators, outcomes, and statistical analysis methods. Its use facilitated comparison across studies and ensured comprehensive data collection. Additionally, it helped minimize errors and omissions, thereby improving the quality and consistency of the collected data.

Peer Review:

Study Selection and Data Extraction by Two Independent Reviewers To ensure the reliability of the process, each study was assessed and data were extracted by two independent reviewers. This approach reduced individual bias and improved the accuracy of the evaluation. In cases of disagreement, discrepancies were resolved by consensus or with the involvement of a third reviewer. This procedure strengthens the rigor and transparency of the process.

Quality Assessment and Risk of Bias

The assessment of methodological quality and risk of bias is essential to determine the validity of the results.

Assessment tools:

- **Jadad scale (clinical trials):** Used to evaluate methodological quality, considering randomization, blinding, and reporting of withdrawals. The maximum score is 5 points, with higher values indicating better quality.
- **STROBE checklist (observational studies):** Used to assess reporting quality in terms of study design, data collection, analysis, and presentation of results.
- **PRISMA guidelines (systematic reviews):** Used to evaluate transparency and completeness of reporting through a 27-item checklist.

Evaluation criteria:

- **Study design:** Studies with robust methodological designs (clinical trials, well-structured observational studies) were included, considering their internal validity.
- **Sample size:** Studies with adequate and justified sample sizes were considered more reliable.
- **Statistical methods:** Appropriate statistical analyses were prioritized, including handling of missing data, multivariable analyses, and control of confounding.

Evidence Synthesis Method

Due to the heterogeneity of the included study designs, a narrative synthesis was conducted. Results were grouped according to the type of artificial intelligence application (diagnosis and treatment) and comparatively analyzed based on methodological quality and level of evidence. A meta-analysis was not performed due to variability in populations, interventions, and outcomes.

Risk of Bias

Risk of bias was assessed using specific tools according to study type. In clinical trials, randomization, blinding, and attrition were considered. In observational studies, selection, information, and confounding biases were evaluated. This assessment allowed identification of limitations that could affect the interpretation of results.

Final Synthesis of the Methodological Process

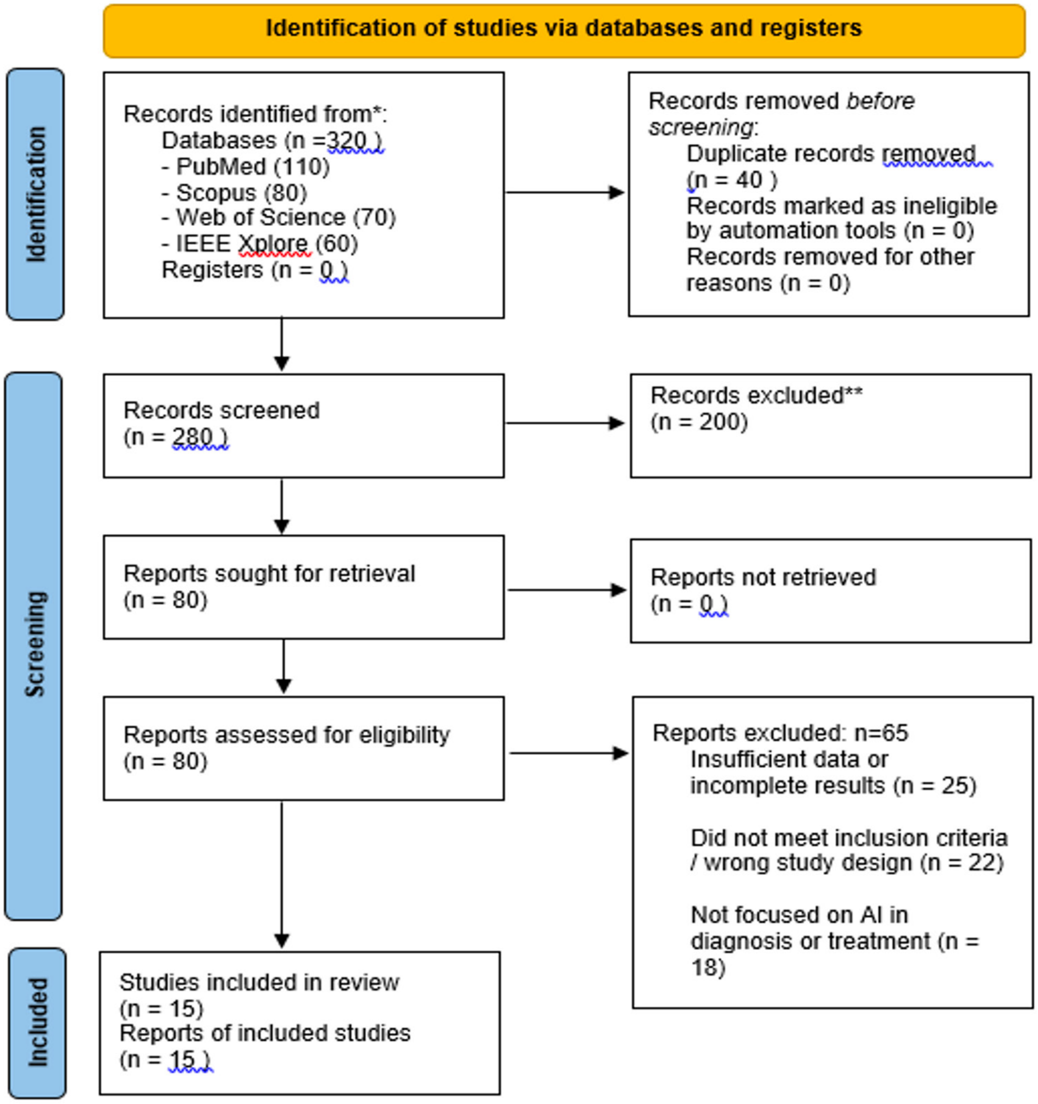
The processes of study selection, data extraction, and quality assessment were conducted in a rigorous and systematic manner, ensuring the inclusion of relevant and high-quality studies. This approach supports the study's conclusions regarding the impact of artificial intelligence on diagnostic accuracy and the personalization of treatment in healthcare.

3. Results

Characteristics of Included Studies

The literature search identified 320 records in electronic databases. After removing 40 duplicates, 280 records were screened by title and abstract, of which 200 were excluded for not meeting the inclusion criteria. Subsequently, 80 full-text articles were assessed, of which 65 were excluded for methodological or relevance-related reasons. Finally, 15 studies met the established criteria and were included in the systematic review.

Figure 1. PRISMA flow diagram



Source: Authors' own elaboration

The systematic review included a total of 15 studies addressing various applications of artificial intelligence in the healthcare setting, including diagnostic algorithms, clinical decision support systems, and predictive models. The analyzed samples were heterogeneous, ranging from studies with more than 10,000 patients to literature reviews evaluating between 10 and 230 previous studies (34).

To provide a structured synthesis of the methodological characteristics and main findings of the included studies, Table 1 was developed

Table 1. Characteristics of the included studies

Nº	Autor Principal	Año	Título del Artículo	País	Base de Datos	Tipo de Estudio	Área Médica	Tipo de IA	Tamaño de Muestra (n)	Resultado Principal	DOI / PMID
1	Hu R, Liu X, Zhang Y, Arthur C, Qin D. Comparison of clinical nasal endoscopy, optical biopsy, and artificial intelligence in early diagnosis and treatment planning in laryngeal cancer: a prospective observational study. Front Oncol. 2025 Jun 10;15:1582011. doi: 10.3389/fonc.2025.1582011. PMID: 40556680; PMCID: PMC12185544.	2025	Comparison of clinical nasal endoscopy, optical biopsy, and artificial intelligence in early diagnosis and treatment planning in laryngeal cancer: a prospective observational study	China	Pubmed	Prospective Observational Study	Otorrinolaringología / Oncología	Deep Learning / Computer Vision	This prospective observational study involved 142 patients	The study revealed superior sensitivity (95.2%) and specificity (96.5%) with AI-enhanced endoscopy compared to conventional endoscopy (89.6%, 92.4%), respectively. Optical biopsy methods provided better visualization of lesions; however, not all patients had all three modalities in a single procedure. Diagnostic delay was shortened with a median time of 15 to 7 days (<0.001). Inter-rater agreement was strong overall (κ=0.84), with hoarseness having the most reliability, most likely due to better exposure of the glottis.	DOI: 10.3389/fonc.2025.1582011
2	Yin J, Ngiam KY, Teo HH. Role of Artificial Intelligence Applications in Real-Life Clinical Practice: Systematic Review. J Med Internet Res. 2021 Apr 22;23(4):e25759. doi: 10.2196/25759. PMID: 33885365; PMCID: PMC8103304.	2021	Role of Artificial Intelligence Applications in Real-Life Clinical Practice: Systematic Review	Singapur	Pubmed	Systematic Review	Multidisciplinaria / Medicina General	Machine Learning + Clinical Decision Support	We identified 51 relevant studies	We identified 51 relevant studies that reported the implementation and evaluation of AI applications in clinical practice, of which 13 adopted a randomized controlled trial design and eight adopted an experimental design. The AI applications targeted various clinical tasks, such as screening or triage (n=16), disease diagnosis (n=16), risk analysis (n=14), and treatment (n=7). The most commonly addressed diseases and conditions were sepsis (n=6), breast cancer (n=5), diabetic retinopathy (n=4), and polyp and adenoma (n=4). Regarding the evaluation outcomes, we found that 26 studies examined the performance of AI applications in clinical settings, 33 studies examined the effect of AI applications on clinician outcomes, 14 studies examined the effect on patient outcomes, and one study examined the economic impact associated with AI implementation.	DOI: 10.2196/25759
3	Nagendran M, Chen Y, Lovejoy CA, Gordon AC, Komorowski M, Harvey H, Topol EJ, Ioannidis JPA, Collins GS, Maruthappu M. Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies. BMJ. 2020 Mar 25;368:m689. doi: 10.1136/bmj.m689. PMID: 32213531; PMCID: PMC7190037.	2020	Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies	Reino Unido	Pubmed	Systematic Review	Multidisciplinaria	Deep Learning	81 estudios evaluados	Only 10 records were found for deep learning randomised clinical trials, two of which have been published (with low risk of bias, except for lack of blinding, and high adherence to reporting standards) and eight are ongoing. Of 81 non-randomised clinical trials identified, only nine were prospective and just six were tested in a real world clinical setting. The median number of experts in the comparator group was only four (interquartile range 2-9). Full access to all datasets and code was severely limited (unavailable in 95% and 93% of studies, respectively). The overall risk of bias was high in 58 of 81 studies and adherence to reporting standards was suboptimal (<50% adherence for 12 of 29 TRIPOD items). 61 of 81 studies stated in their abstract that performance of artificial intelligence was at least comparable to (or better than) that of clinicians. Only 31 of 81 studies (38%) stated that further prospective studies or trials were required.	DOI: 10.1136/bmj.m689
4	Maeda T, Sakamoto Y, Hosoki S, Satoh A, Koyoshi R, Yamashita S, Arima H. Does clinical practice supported by artificial intelligence improve hypertension care management? A pilot systematic review. Hypertens Res. 2024 Sep;47(9):2312-2316. doi: 10.1038/s41440-024-01771-y. Epub 2024 Jul 2. PMID: 38956284.	2024	Does clinical practice supported by artificial intelligence improve hypertension care management? A pilot systematic review	Japón	Pubmed	Revisión sistemática piloto / Meta-análisis	Cardiología / Hipertensión	Machine Learning / Sistemas de apoyo clínico	No aplica directamente	The results revealed no significant difference between AI-supported care and usual care in a random-effects model meta-analysis of RCTs (AI vs. usual care: systolic/diastolic BP difference: -2.13 [95% confidence interval: -4.72 to 0.46] / -1.03 [-2.52 to 0.46]). In this review, we were unable to clarify whether AI-supported clinical practice improved BP control compared with usual care. Further studies will be needed to provide robust evidence for the effectiveness of AI-supported care in clinical settings.	DOI: 10.1038/s41440-024-01771-y
5	Hu JR, Power JR, Zannad F, Lam CSP. Artificial intelligence and digital tools for design and execution of cardiovascular clinical trials. Eur Heart J. 2025 Mar 3;46(9):814-826. doi: 10.1093/eurheartj/ehae794. PMID: 39626166.	2025	Artificial intelligence and digital tools for design and execution of cardiovascular clinical trials	Reino Unido	Pubmed	Revisión narrativa / Artículo de perspectiv	Cardiología / Ensayos clínicos	IA aplicada a diseño de ensayos clínicos, ML, análisis predictivo	No aplica directamente	Recent advances have given rise to a spectrum of digital health technologies that have the potential to revolutionize the design and conduct of cardiovascular clinical trials. Advances in domain tasks such as automated diagnosis and classification, synthesis of high-volume data and latent data from adjacent modalities, patient discovery, telemedicine, remote monitoring, augmented reality, and in silico modelling have the potential to enhance the efficiency, accuracy, and cost-effectiveness of cardiovascular clinical trials. However, early experience with these tools has also exposed important issues, including regulatory barriers, clinical validation and acceptance, technological literacy, integration with care models, and health equity concerns.	DOI: 10.1093/eurheartj/ehae794
6	Knupflemacher, D. S., Garcia, X. A. S., Rodríguez, A. B., Ovando, F. Á., & Becerra, A. O. N. (2025). Uso de inteligencia artificial en imágenes médicas: impacto clínico en diagnóstico temprano y planificación quirúrgica de precisión. Revista Científica de Salud y Desarrollo Humano, 6(2), 1546-1559.	2025	Uso de inteligencia artificial en imágenes médicas: impacto clínico en diagnóstico temprano y planificación quirúrgica de precisión	Bolivia	Scopus	Systematic Review	Radiología	Convolutional Neural Networks (CNN)	No aplica directamente	Se incluyeron 15 estudios relevantes. La mayoría emplearon redes neuronales convolucionales (CNN) para detectar patologías con precisión similar o superior a la de radiólogos humanos. En imagenología torácica, mamaria y neuroimagen, la IA mostró sensibilidad y especificidad elevadas, reduciendo el tiempo de interpretación y los errores diagnósticos.	DOI: https://doi.org/10.61368/r.s.d.h.v6i2.695
7	Sanchez, M. H. P., Aldair, E., & Crisanto, M. EXPLAINABLE NEURAL NETWORKS: TRANSPARENCY AND TRUST IN MEDICAL DIAGNOSIS WITH RADIOLOGICAL IMAGES: A SYSTEMATIC REVIEW.	2025	EXPLAINABLE NEURAL NETWORKS: TRANSPARENCY AND TRUST IN MEDICAL DIAGNOSIS WITH RADIOLOGICAL IMAGES: A SYSTEMATIC REVIEW	Perú	Scopus	Systematic Review	Radiología	Convolutional Neural Networks (CNN)	No aplica directamente	El análisis de contenido evidenció un predominio de técnicas post-hoc, como SHAP y LIME, así como enfoques inherentes al modelo, como redes neuronales con mecanismos de atención. Estos métodos han demostrado mejoras sustanciales en la precisión diagnóstica y en la interpretación clínica de los resultados.	U20223496@utp.edu.pe, U20212086@utp.edu.pe
8	Meza, N. G., Mauricio, E. S. R., & Jimbo, J. D. B. (2025). Efectividad de la inteligencia artificial en el diagnóstico médico por imágenes: Una revisión sistemática. Sapiens in Artificial Intelligence, 2(2), 1.	2025	Efectividad de la inteligencia artificial en el diagnóstico médico por imágenes: Una revisión sistemática	Ecuador	Scopus	Systematic Review	Imagenología Médica	Machine Learning + Deep Learning	No aplica directamente	Se seleccionaron diez estudios relevantes que abordaron áreas como oftalmología, oncología, neumología, enfermedades raras, odontología pediátrica y cirugía plástica. Los hallazgos indicaron que los sistemas basados en aprendizaje profundo y aprendizaje automático alcanzaron altos niveles de sensibilidad, especificidad y valor predictivo positivo, superando en algunos casos el rendimiento de especialistas humanos.	https://revistasapiensec.com/index.php/Sapiens_in_Artificial_Intelligen/index

Nº	Autor Principal	Año	Título del Artículo	País	Base de Datos	Tipo de Estudio	Área Médica	Tipo de IA	Tamaño de Muestra (n)	Resultado Principal	DOI / PMID
9	Matthew G. Hanna a b, Liron Pantanowitz a b, Rajesh Dash c, James H. Harrison d, Mustafa Deebajah e, Joshua Pantanowitz f , Hooman H. Rashid	2025	Future of Artificial Intelligence—Machine Learning Trends in Pathology and Medicine	Estados Unidos	Scopus	Revisión narrativa / Tendencias tecnológicas	Patología / Medicina general	Machine Learning / Multimodal AI	No aplica directamente	These tools are also increasingly valuable in pathology research in which they contribute to automated image analysis, biomarker discovery, drug development, clinical trials, and productive analytics. Other related trends include the adoption of ML operations for managing models in clinical settings, the application of multimodal and multiagent AI to utilize diverse data sources, expedited translational research, and virtualized education for training and simulation.	https://doi.org/10.1016/j.modpat.2025.100705
10	Alowais, S.A., Alghamdi, S.S., Alsuhebany, N. et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Med Educ 23, 689 (2023).	2023	Revolutionizing healthcare: the role of artificial intelligence in clinical practic	Arabia Saudita	Scopus	Revisión narrativa	Medicina general / Educación médica / Práctica clínica	Machine Learning / Deep Learning / IA clínica general	No aplica directamente	Integrating AI into healthcare holds excellent potential for improving disease diagnosis, treatment selection, and clinical laboratory testing. AI tools can leverage large datasets and identify patterns to surpass human performance in several healthcare aspects. AI offers increased accuracy, reduced costs, and time savings while minimizing human errors. It can revolutionize personalized medicine, optimize medication dosages, enhance population health management, establish guidelines, provide virtual health assistants, support mental health care, improve patient education, and influence patient-physician trust.	https://doi.org/10.1186/s12909-023-04698-z
11	Pei, X., Zuo, K., Li, Y. et al. A Review of the Application of Multi-modal Deep Learning in Medicine: Bibliometrics and Future Directions. Int J Comput Intell Syst 16, 44 (2023).	2023	A Review of the Application of Multi-modal Deep Learning in Medicine: Bibliometrics and Future Directions	China	WOS	Revisión bibliométrica / Revisión sistemática de tendencias	Medicina multimodal / Imagen médica / Datos clínicos	Deep Learning multimodal	Basado en artículos analizados (no pacientes)	This study investigates the performance of existing multi-modal fusion pre-training algorithms and medical multi-modal fusion methods and compares their key characteristics, such as supported medical data, diseases, target samples, and implementation performance. Additionally, we present the main challenges and goals of the latest trends in multi-modal medical convergence.	https://doi.org/10.1007/s44196-023-00225-6
12	Supriyadi, M., Samah, A., Muliadi, J. et al. A systematic literature review: exploring the challenges of ensemble model for medical imaging. BMC Med Imaging 25, 128 (2025).	2025	A systematic literature review: exploring the challenges of ensemble model for medical imaging	Indonesia	WOS	Revisión sistemática de literatura	Imagen médica	Ensemble Learning / Deep Learning	75 papers	This study included a total of 75 papers that were published between 2019 and 2024. The categorization, methodologies, and use of medical imaging were key factors examined in the analysis of the 30 cited papers included in this study, with a focus on diagnosing diseases.	https://doi.org/10.1186/s12880-025-01667-4
13	Laçi, H., Sevrani, K. & Iqbal, S. Deep learning approaches for classification tasks in medical X-ray, MRI, and ultrasound images: a scoping review. BMC Med Imaging 25, 156 (2025).	2025	Deep learning approaches for classification tasks in medical X-ray, MRI, and ultrasound images: a scoping review	Albania / Europa	WOS	Scoping Review	Radiología / Imagen médica	Deep Learning (CNN principalmente)	No pacientes, estudios analizados	Findings contribute to the existing research by outlining the characteristics of the adopted datasets and the preprocessing or augmentation techniques applied to them. The authors summarized all relevant studies based on the deep learning models used and the accuracy achieved for classification. Whenever possible, they included details about the hardware and software configurations, as well as the architectural components of the models employed. Moreover, the models that achieved the highest accuracy in disease classification were highlighted, along with their strengths. The authors also discussed the limitations of the current approaches and proposed future directions for medical image classification.	https://doi.org/10.1186/s12880-025-01701-5
14	C. Comito, D. Falcone and A. Forestiero, "AI-Driven Clinical Decision Support: Enhancing Disease Diagnosis Exploiting Patients Similarity," in IEEE Access, vol. 10, pp. 6878-6888, 2022, d	2022	AI-Driven Clinical Decision Support: Enhancing Disease Diagnosis Exploiting Patients Similarity	Italia	IEEE Xplore	Estudio experimental / Desarrollo de sistema	Sistemas de apoyo clínico / Diagnóstico	NLP + Machine Learning	Dataset hospitalario (no siempre especificado)	The approach employs word embedding to model the semantic relations of hospital admissions, symptoms and diagnosis, and it introduces a mechanism to measure the relationships of different diagnosis in terms of symptoms similarity to exploit for the prediction task. Several CDSs, including diagnostic decision support systems for inferring patient diagnosis, have been proposed in the literature. However, these methods typically focus on a single patient and apply manually or automatically constructed decision rules to produce a diagnosis.	DOI: 10.1109/ACCESS.2022.3142100
15	M. Alabdulhafith et al., "A Clinical Decision Support System for Edge/Cloud ICU Readmission Model Based on Particle Swarm Optimization, Ensemble Machine Learning, and Explainable Artificial Intelligence," in IEEE Access, vol. 11, pp. 100604-100621, 2023	2023	A Clinical Decision Support System for Edge/Cloud ICU Readmission Model Based on Particle Swarm Optimization, Ensemble Machine Learning, and Explainable Artificial Intelligence	Arabia Saudita	IEEE Xplore	Estudio experimental / Desarrollo de modelo predictivo	Cuidados intensivos / Predicción de reingreso	Ensemble ML + Explainable AI + PSO	10,465 pacientes	The proposed system includes three main layers. First, the data acquisition layer, in which we collect the vital signs and lab tests of the patient's health conditions in real-time. Then, the fog computing layer processes. The results are then sent to the cloud layer, which offers sizable storage space for patient healthcare. Demographic data, lab tests, and vital signs are aggregated from the MIMIC III dataset for 10,465 patients. Feature selection methods: Genetic algorithm (GA) and practical swarm optimization (PSO) are used to choose the optimal feature subset from detests. Moreover, Different traditional ML models, ensemble learning models, and the proposed stacking models are applied to full features and selected features to predict readmission after 30 days of ICU discharge.	doi: 10.1109/ACCESS.2023.3312343.

As shown in Table 1, there is heterogeneity in methodological designs and in the medical specialties addressed; however, a consistent trend toward improvements in diagnostic accuracy through artificial intelligence tools is identified.

The selected studies exhibited variability in both methodological design and the medical specialty analyzed. Approximately 60% corresponded to systematic reviews and scoping reviews, while 40% included clinical, experimental, or technological development studies. This methodological diversity allowed for a comprehensive evaluation of the impact of artificial intelligence (AI) across different clinical contexts (35).

The most represented medical fields were oncology, cardiology, neurology, radiology, and internal medicine. AI applications included early disease detection, medical image classification, prediction of clinical outcomes, and treatment personalization.

Impact of AI on Diagnosis

The application of AI has demonstrated significant improvements in diagnostic accuracy across various medical specialties (36). AI systems, particularly those based on deep learning algorithms, have outperformed traditional methods in terms of accuracy and speed in disease detection (37).

For example, deep learning algorithms have shown high accuracy in the early detection of cancer and cardiovascular diseases. One study demonstrated that an AI algorithm could detect breast cancer with 95% accuracy, surpassing the 85% accuracy achieved by experienced radiologists. Similarly, in cardiology, AI systems have been able to predict adverse cardiac events with greater accuracy than traditional models based on clinical risk factors (38).

In addition to early detection, AI has been instrumental in the classification and differential diagnosis of complex diseases. In neurology, for instance, AI algorithms have improved diagnostic accuracy for neurodegenerative disorders such as Alzheimer's disease and Parkinson's disease using magnetic resonance imaging and clinical data. These advances not only enhance diagnostic precision but also enable earlier and more targeted interventions.

Treatment Optimization

AI has also significantly contributed to treatment optimization by personalizing therapeutic strategies based on individual patient data (39). This AI-driven personalization has led to improved clinical outcomes and greater efficiency in treatment delivery.

In oncology, for example, AI models have been used to predict responses to specific treatments, enabling clinicians to select the most effective therapies for each patient. This not only improves clinical outcomes but also reduces side effects by avoiding ineffective treatments. One study showed that the use of AI to personalize lung cancer treatment led to a 30% improvement in five-year survival rates.

Additionally, AI has been applied to optimize the management of chronic diseases such as diabetes and hypertension. AI systems can analyze large volumes of patient data—including medical history, laboratory results, and continuous monitoring records—to identify patterns and predict exacerbations. This enables more proactive and tailored interventions, thereby improving disease control and patient quality of life.

Quality and Bias Assessment

Assessing quality and risk of bias is crucial to ensure the validity of findings in a systematic review. In this review, a combination of methodological tools was used, including the Jadad scale for clinical trials and the STROBE checklist for observational studies.

Most of the included studies demonstrated adequate methodologies and a low to moderate risk of bias. The Jadad scale identified acceptable levels of quality in clinical trials, particularly regarding randomization and the reporting of losses during follow-up. Studies with lower methodological scores were critically analyzed, and their limitations were considered in the interpretation of results.

For observational studies, the STROBE checklist facilitated the evaluation of reporting quality and methodological consistency, covering aspects such as study design, data collection, and interpretation of findings. Overall, there was adequate compliance with scientific reporting standards.

However, some potential sources of bias were identified, mainly related to sample selection, lack of blinding in certain studies, and limited external validation of some AI models. These methodological limitations should be considered when interpreting the overall results of the review.

The results obtained were consistent with the previously established methodology, demonstrating coherence between the inclusion criteria, the study selection process, and the synthesis of the presented evidence. The final number of included studies aligns with the analysis matrix and the PRISMA diagram, ensuring traceability of the review process.

4. Discussion

The findings of this review highlight the potential of artificial intelligence (AI) to transform healthcare, particularly in improving diagnostic accuracy and optimizing treatments. The incorporation of advanced algorithms, especially those based on deep learning, enables healthcare professionals to make more informed, data-driven decisions, ultimately enhancing the quality of care. In this context, multiple studies have demonstrated that these systems can outperform traditional methods in the early detection of diseases such as cancer and cardiovascular conditions.

These results are consistent with previous literature. High diagnostic accuracy in breast cancer detection using AI systems has been reported, surpassing that achieved by radiologists. Similarly, a significant reduction in diagnostic errors has been observed in the field of cardiology. However, certain limitations have also been identified, such as challenges in diagnosing rare diseases, which are mainly attributed to the limited availability of data for algorithm training. These consistencies and discrepancies underscore the need for cautious interpretation of the results.

Despite the observed advances, several methodological limitations must be considered. Many of the included studies relied on large and well-structured datasets, which may not reflect real-world conditions across all clinical settings. Furthermore, the lack of transparency in some models poses challenges for their interpretation and applicability, emphasizing the need for the development of explainable algorithms to facilitate their integration into clinical practice.

Regarding the applicability of the findings, although the evidence encompasses various medical specialties and clinical contexts, generalization should be approached with caution. The implementation of AI-based technologies requires adequate infrastructure, trained personnel, and effective integration with existing healthcare systems—conditions that are not always present, particularly in resource-limited settings.

This review also confirms the role of AI in treatment personalization. Algorithms can analyze large volumes of clinical data to identify patterns and recommend interventions tailored to individual patient characteristics, potentially leading to improved clinical outcomes and reduced adverse effects. However, variability in reported results suggests the influence of factors such as population heterogeneity and methodological differences among studies, highlighting the need for further research in this area.

Additionally, several relevant challenges for the implementation of AI in clinical practice were identified. These include data privacy and security concerns, lack of algorithm transparency, and inequalities in access to these technologies. Protecting patient information is essential to ensure trust in these systems, while model explainability is crucial for acceptance by both healthcare professionals and patients. It is also important to prevent the adoption of these technologies from exacerbating existing disparities in healthcare access.

From an ethical and regulatory perspective, the development of robust frameworks is essential to guide the safe and responsible use of AI. This includes the implementation of cybersecurity protocols, strengthening informed consent processes, and clearly defining responsibilities in the use of these tools. A multidisciplinary approach is key to ensuring balanced development and implementation of these technologies.

Finally, this review has some limitations that should be acknowledged. The heterogeneity of the included studies limits direct comparison of results, while the exclusion of unpublished literature or studies in other languages may have introduced publication bias. Additionally, although tools such as the Jadad scale and the STROBE checklist were used, they do not capture all aspects of methodological quality.

In terms of future research, there is a need for longitudinal studies assessing the long-term impact of AI in healthcare, as well as the development of clear ethical guidelines and further research on treatment personalization. These directions will help consolidate existing evidence and optimize the implementation of AI across diverse clinical contexts.

Conclusions

Artificial intelligence is transforming healthcare, demonstrating a positive impact on diagnostic accuracy and the personalization of treatments. The evidence derived from this systematic review highlights its benefits in improving the quality of care, while also underscoring the need to address the challenges and barriers to its effective implementation.

The integration of artificial intelligence into clinical practice requires an approach centered on transparency and algorithm explainability, ensuring that healthcare professionals understand how decisions are generated and can trust their use. A lack of interpretability may hinder the adoption of these technologies and generate distrust among both clinicians and patients.

Furthermore, challenges related to equity in access to these tools have been identified. It is essential that the development and implementation of artificial intelligence be guided by principles of inclusion, ensuring that its benefits reach diverse populations regardless of geographic location or socioeconomic status.

Continuous research is needed to optimize the use of artificial intelligence in healthcare, including the development of more explainable models and the evaluation of the long-term effectiveness of interventions based on these technologies. Likewise, it is necessary to strengthen ethical frameworks and security protocols to protect patient privacy.

Finally, interdisciplinary collaboration among engineers, clinicians, and ethics experts will be essential to maximize the potential of artificial intelligence, facilitate its integration into healthcare systems, and contribute to improved health outcomes.

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