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IMPACT OF ARTIFICIAL INTELLIGENCE ON MEDICINE: BIBLIOGRAPHICAL REVIEW ON DIAGNOSIS, TREATMENT AND DECISION SUPPORT SYSTEMS

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ABSTRACT
The use of artificial intelligence (AI) in medicine has grown substantially, impacting areas such as imaging diagnosis, treatment prediction, and electronic medical record analysis. This literature review aimed to explore the use of AI in the diagnosis and treatment of diseases, highlighting methodologies and applications in different areas of health. Fifty-seven articles on the integration of AI in oncology, cardiology, and emergency medicine were analyzed. AI has been widely applied in clinical decision support systems, such as dynamic Bayesian networks to predict disease progression and treatment outcomes. The review revealed benefits, such as greater diagnostic accuracy and efficiency, but challenges related to transparency and trust in AI models persist. Many studies have employed machine learning and deep learning, integrating longitudinal data from medical records. It is concluded that AI has the potential to transform medical practice, but requires rigorous validation and supervision.

Keywords: Artificial Intelligence. Predictive Models. Diagnosis. Machine Learning. Health.

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INTRODUCTION

Artificial intelligence (AI) has established itself as an essential tool in modern medicine, with applications ranging from supporting imaging diagnostics to large-scale data analysis and personalized treatments. In the clinical context, AI has been used to improve diagnostic accuracy and healthcare efficiency, enabling the analysis of large volumes of data, such as electronic medical records, quickly and efficiently. The relevance of this topic is highlighted by its potential to transform medical practice, especially in critical areas such as oncology, cardiology, and medical emergencies (Carrasco-Ribelles et al., 2023). The central problem of this study is to understand how AI is being integrated into healthcare systems, what the real benefits of this integration are, and what challenges still exist, such as issues related to transparency and trust in algorithms. The lack of clarity in AI models and the need for rigorous validation are aspects that limit the broader application of these technologies (Sariyar & Holm, 2022). Thus, this article aims to comprehensively review the current literature on the application of AI in medicine, focusing on its contributions to the diagnosis and treatment of diseases. The research seeks to consolidate the evidence on the benefits of AI and identify the main barriers that need to be overcome for its full adoption.

The relevance of this study lies in its contribution to the understanding of recent advances in the use of AI in various medical specialties, as well as in the identification of areas that require further development, such as the transparency of models and the reliability of AI-assisted decisions (Valêncio et al., 2022). By providing a critical and updated view on the topic, the article hopes to contribute to the development of strategies that maximize the positive impact of AI in medical practice, while addressing the limitations that still restrict its widespread adoption.

THEORETICAL BACKGROUND

The increasing adoption of artificial intelligence (AI) in medicine has been widely discussed in the academic literature, both in the context of diagnostics and in the personalization of treatments. The development of predictive models using machine learning and deep learning has transformed the way healthcare professionals access and interpret clinical data, integrating information from different sources to improve the quality of care. In this context, this theoretical framework explores the main approaches and concepts related to AI applied to medicine, focusing on its implementation, benefits, and challenges.

Research shows a significant increase in the volume of research in the area since 2010, as reported by (Binkheder et al., 2021), which carried out a bibliometric analysis and included 242 publications. Before this period, publications were scarce, with only one publication between 1995 and 1999 and eleven between 2000 and 2009.

AI has been widely studied for its ability to optimize medical processes. According to Carrasco-Ribelles et al. (2023), the integration of AI with longitudinal data from electronic health records allows predicting disease progression and improving clinical decisions (Cresswell et al., 2023), which potentially reduces human error. This approach, based on deep learning predictive models, has proven effective in identifying patterns in large volumes of data, such as those collected in integrated health systems.

METHODOLOGY

The methodology of this study is based on a comprehensive literature review, with an emphasis on the application of artificial intelligence (AI) in health. Articles published between 2018 and the first half of 2024 in the MEDLINE, LILACS, and PubMed of Science databases were selected. The searches were conducted using the following keywords: “Artificial Intelligence” AND “Health”, “Artificial Intelligence” AND “Health” AND Medical Records, “Artificial Intelligence” AND “Health” AND Simulation, and “Artificial Intelligence” AND “Health” AND Personal Health Records.

The inclusion criteria included articles that discussed the use of AI in different clinical contexts, from diagnosis to decision support, including the use of AI in electronic medical records, clinical simulations, and personal health records. Two studies were excluded that did not present practical results or concrete implementations of AI in the health field, as per (Tran et al., 2022) and (Liaw et al., 2021). The selection process resulted in the analysis of 57 articles that make up the basis of discussion for this study. The analysis of the reviewed articles reveals that the most used AI methodologies were machine learning, applied in 72% of the studies, and deep learning, present in 28% of the cases. These approaches allowed the development of predictive models and decision support systems in several health areas.

In addition, some studies used dynamic Bayesian networks and data fusion algorithms, although on a smaller scale. The choice of AI methodology varied according to the objective of each study, but the main focus was always to improve diagnostic accuracy and optimize clinical care. These methods were particularly effective in analyzing large volumes of data, such as electronic medical records and imaging exams, which are essential for personalizing treatments.

As for the application environment, 60% of the studies were conducted in hospital settings, while 30% took place in outpatient settings. The remainder (10%) included research in telemedicine or focused on multiple clinical settings. Regarding the pathologies studied, oncology and cardiology stood out, covering 35% and 25% of the articles, respectively. Neurological diseases represented 15% of the studies, while dermatology and other areas, such as endocrinology and gastroenterology, accounted for the remaining 25%. This distribution highlights the crucial role of AI in the diagnosis and treatment of complex diseases, especially in areas that require high clinical accuracy and personalized predictions.

ANALYSIS AND DISCUSSION

The analysis of the collected data demonstrates that AI plays a central role in transforming medical practice, especially in supporting diagnosis and personalizing treatments. The predominant use of machine learning (72%) and deep learning (28%) among the articles analyzed indicates that these methodologies have been highly effective in extracting complex patterns from large volumes of medical data, such as electronic medical records and imaging exams. This reinforces the idea that AI can significantly improve diagnostic accuracy, as highlighted by (Carrasco-Ribelles et al., 2023), who used predictive models to anticipate the evolution of chronic diseases, and by (Ladyzynski et al., 2022), who applied dynamic Bayesian networks to predict response to treatment in patients with chronic lymphocytic leukemia.

TYPES OF ARTIFICIAL INTELLIGENCE

Machine Learning (ML) is a subset of AI that allows systems to learn and improve from data without being explicitly programmed to perform specific tasks. It works through algorithms that find patterns in data and make predictions based on those patterns. ML is widely used in medical diagnoses, prediction of clinical outcomes and personalization of treatments, as presented in the articles (Mendo et al., 2021), (Maurovich-Horvat, 2021), (Zhu et al., 2022), (Ren et al., 2022), (Strauss et al., 2023), (Rodriguez-Diaz et al., 2022), (Kenner et al., 2021), (Mendo et al., 2021),(Montanaro et al., 2021) (Letterie, 2021), (Morey et al., 2021), (Ho et al., 2022), (Wu et al., 2022), (Reeves et al., 2021), (Kashyap et al., 2021).

Deep Learning (DL) is a subcategory of Machine Learning, characterized by the use of deep neural networks (DNNs) with multiple layers to process large volumes of complex data. This type of AI is particularly effective in recognizing complex patterns, such as medical images and speech. It has been widely used in imaging diagnostics, such as in the detection of cancer and ophthalmological diseases, and is present in the articles of (Rostam

Niakan Kalhori et al., 2021), (Samaras et al., 2023), (Mohsen et al., 2022), (Adler-Milstein et al., 2021).

Natural Language Processing (NLP) is a subcategory of AI that focuses on the interaction between computers and human language, allowing systems to understand, interpret, and respond to human text and speech. In the healthcare sector, NLP has been used to analyze medical records, identify symptoms in patients, and support the completion of medical records, among many other applications such as those presented in (Sagheb et al., 2022), (Mattay et al., 2023), (Riskin et al., 2023), (Shevchenko et al., 2022), (Morin et al., 2021), (Samaras et al., 2023), (Tashman, 2022), (Yao et al., 2021), (Li et al., 2021). Generative Adversarial Networks (GANs) are a type of AI that involves two competing neural network models: a generator, which creates fake data, and a discriminator, which tries to distinguish generated data from real data. This type of AI has been used to improve the robustness of AI systems in medical diagnostics, simulating adverse scenarios and preventing attacks on diagnostic systems (Zhou et al., 2021).

Bayesian networks are probabilistic graphical models that represent a set of variables and their conditional relationships. In the healthcare sector, they are used to predict the progression of diseases and the effects of treatment in chronic conditions, such as lymphocytic leukemia (CLL). ronic (Ladyzynski et al., 2022).

Recurrent Neural Networks (RNNs) are a special type of neural network designed to handle sequential or temporal data. The main characteristic of RNNs is their ability to maintain a “memory” over time, which allows information from previous inputs to influence future outputs. This is particularly useful in healthcare applications, where temporal data, such as vital signs or time series of symptoms, are analyzed (Carrasco-Ribelles et al., 2023).

Explainable AI (XAI) is a branch of AI that focuses on making AI models more understandable to humans by providing explanations about how decisions or predictions were made. In the healthcare sector, this is crucial to increase doctors’ confidence in the predictions made by algorithms (Sariyar & Holm, 2022).

In (Clement & Maldonado, 2021), study presents the use of AI to assist in clinical decisions in solid organ transplantation. AI is used to analyze large volumes of clinical data, including biomarkers and patient histories, providing personalized predictions for immunosuppression regimens. One of the main benefits mentioned is the ability of AI to identify patterns and make predictions that may not be easily detectable by humans. The study highlights the importance of overcoming challenges related to the transparency and explainability of AI algorithms, in addition to suggesting the creation of teams dedicated to the integration of AI in transplant centers, promoting the ethical and effective use of these tools in clinical practice.

However, challenges related to trust in AI systems, particularly about “black box” models, remain significant. Sariyar and Holm (2022) argue that the lack of explainability of AI algorithms, a common phenomenon in advanced models such as deep neural networks, limits the trust of healthcare professionals in these systems, especially in clinical scenarios where critical decisions need to be made quickly. The analysis suggests that the implementation of explainable AI (XAI) can mitigate these concerns by making decisions more transparent and interpretable.

PREDICTIVE MODELS AND CLINICAL DECISION SUPPORT

Predictive models have played a crucial role in personalizing treatment and predicting outcomes in patients with serious conditions such as cancer and heart disease. According to (Ladyzynski et al., 2022), the use of dynamic Bayesian networks in patients with chronic lymphocytic leukemia has allowed prediction of treatment response and prognosis based on clinical factors, contributing to more informed therapeutic decisions. This use of predictive models illustrates the potential of AI in handling complex medical data and personalizing healthcare. However, it is important to highlight that these models are not without limitations. According to (Jain et al., 2021), AI applied to dermatology in telemedicine practices has demonstrated increases in diagnostic accuracy, but still faces barriers, such as variability in human assessments. Overreliance on AI systems, without proper validation by human experts, can lead to diagnostic errors, highlighting the need for continuous oversight of the models.

(Khoury et al., 2022) emphasizes that a framework is needed to evaluate, approve, and monitor the impact of these technologies. They highlight the importance of the active participation of experts in the development, validation, and implementation of AI systems in the field of allergy and immunology, in addition to discussing the challenges related to AI governance, education, and ethical issues, including equity in the use of these technologies.

The article suggests that multidimensional data, both from electronic health records and immunological datasets, can be significantly reduced and analyzed to provide clinical decision support. However, to ensure the appropriate application of these technologies, professionals in the field must be involved throughout the process.

CHALLENGES AND LIMITATIONS

While AI offers numerous benefits, its implementation in medicine also poses significant challenges. One of the main challenges is ensuring the quality of input data since algorithms rely heavily on both the quantity and quality of data to provide accurate predictions. (Akay et al., 2023) and (Bajgain et al., 2023) add to the need for a review that focuses on how AI-based systems can be developed to improve clinical decision support by correlating patient characteristics with outcomes, thus helping clinicians make informed decisions. Although there is significant potential, there are threats to validity and challenges in clinical translation.

Heterogeneity in data collection methods and reporting practices are highlighted as major obstacles to be overcome for effective implementation. Furthermore, there are ethical and regulatory concerns regarding the use of AI in clinical settings, as highlighted in (Maurud et al., 2023), particularly about patient privacy and accountability for automated decisions.

In (Gellert, 2023), paper explores how the increasing use of medical record assistants may be impacting the evolution of AI in electronic health records (EHRs). The AI discussed in the paper is primarily related to automation and the ability of EHRs to integrate new clinical evidence and facilitate efficient medical practice.

The paper argues that medical record assistants while increasing productivity and workflow efficiency for clinicians, may be slowing the progress of AI in EHRs by disconnecting clinicians from the process of system evolution. He suggests that the use of medical record assistants may isolate healthcare professionals from the ongoing learning that occurs with AI embedded in electronic records, which could hinder the advancement of AI in healthcare.

According to (Sariyar & Holm, 2022), trust in AI systems is another critical issue. Healthcare professionals are often hesitant to adopt these technologies due to the lack of transparency in the algorithms' decision-making processes. To overcome these challenges, AI developers should prioritize creating systems that not only demonstrate high accuracy but also provide clear explanations for their predictions to increase trust and acceptance among clinicians.

In (Lim et al., 2022), explores the opinions of 603 patients on the use of artificial intelligence (AI) in diagnosing skin cancer. The survey revealed that 47% of respondents were not opposed to the use of AI to assist skin specialists in making a diagnosis. However, 81% felt it was important for a dermatologist to confirm the diagnosis and discuss the results with them. The study concludes that, although patients accept the use of AI as a support tool, interaction with the physician continues to be valued, highlighting the importance of the dermatologist's presence during the diagnostic process. However, there is still resistance to adopting new technologies, as in (Samaran et al., 2021) who examined the difficulties faced by French general practitioners in diagnosing non-melanoma skin cancer and assessed their interest in using artificial intelligence tools to help in this process. The survey, which included 147 physicians, revealed that 98% face difficulties in these diagnoses, and 86% believe that an AI tool would be useful in the office. However, 68% would not be willing to pay for this type of software, highlighting that interest in AI is high, but cost and accessibility are important barriers to its adoption. In the article (Dobson et al., 2023), the authors examine patients' perceptions about the secondary use of their health information, beyond immediate care. The research used semi-structured interviews with health service users in New Zealand. The interviews explored scenarios around the use of health information, including current practices, artificial intelligence, machine learning, clinical calculators, surveys, registries, and public health surveillance. The results revealed four main themes: helping others, sharing data as important, trust, and respect. Participants supported the use of their health information to help others and advance science, but placed conditions, especially related to trust in health institutions to protect their data and ensure that it is not used in harmful ways. (Xu et al., 2023) and (Jeong & Kamaleswaran, 2022), argue that interpretability is crucial for the acceptance of clinical decision support systems in the clinical setting since health professionals need to trust the results generated by these systems. In addition, challenges related to data complexity and the use of “black box” models, such as deep neural networks, which hinder transparency, are discussed.

POTENTIAL OF AI IN MEDICINE

The potential of AI to transform medical practice is immense. According to (Carrasco-Ribelles et al., 2023), one promising area is the development of models that can integrate data from multiple sources, such as health records, genomics, and sensor data, to provide a more holistic view of a patient's health. This approach would not only improve diagnoses but also enable more accurate and timely interventions.

The article (Mazzu-Nascimento et al., 2022) explores the use of smartphones as tools for noninvasive screening of cardiovascular diseases. The authors highlight that smartphones, equipped with cameras, microphones, espresso machines, and an internet connection can be used to perform optical, electrical, and acoustic analyses of cardiovascular signals, such as heart rate, blood pressure, and oxygen saturation, as well as detect cardiac murmurs and electrical conduction.

Artificial intelligence is a central part of these innovations, as signal processing and machine learning (ML) algorithms are used to interpret the data obtained through smartphone sensors. The study argues that these tools can help improve access to healthcare and cardiovascular disease screening in vulnerable populations, especially in remote or resource-limited areas, where access to traditional medical services is restricted.

An interesting point raised by (Helman et al., 2022) is related to the ease of use of technologies, the focus was on the development of a graphical interface for an intelligent bedside alert system, used to support clinical decisions in real-time. AI plays a central role in processing clinical data and generating alerts that indicate possible cardiorespiratory failures.

The authors argue that active participation by clinicians from the beginning of the interface design process is essential to optimize the efficiency of the system and ensure that it integrates effectively into the clinical workflow. The methodology involved focus groups with 23 clinicians, who provided feedback on the prototype of the graphical interface, which resulted in adjustments to the display of alerts, such as the customization of thresholds and the integration of contextual information. The results suggest that early engagement of clinical users in the development of AI systems for decision support improves the acceptance and practical utility of these systems in daily medical practice.

In (Ronquillo et al., 2022) the underutilized potential of data from nursing and other allied health professions to improve the representation of social determinants of health and intersectionality in electronic health records is discussed. The article argues that the contextual richness of the data collected by these professionals can help to better capture the nuances of social determinants of health and intersectionality, allowing AI applications to be more inclusive and accurate. A challenge presented by (Daley et al., 2022) is that despite the evolution of technologies, there are still few applications that integrate AI for decision support, and many applications only record data such as blood glucose levels and provide generic education, without the use of artificial intelligence to personalize care.

In (De Bie et al., 2021) a digital clinical decision support tool (Digital Clinical Checklist - DCC) is used to improve adherence to best practices in the ICU. Although the study mentioned the use of a dynamic digital checklist, the use of AI techniques such as machine learning or neural networks was not made explicit.

A very promising case is presented in (Lee et al., 2022) where it is reported that most hospitals in South Korea have implemented electronic medical record systems, with 100% adoption in tertiary hospitals and 90.5% in smaller hospitals. However, the implementation of personal health records varied significantly depending on the size of the institution. The paper also discusses the use of secondary medical data, such as clinical data warehouses and shared data models, noting that more than half of tertiary hospitals have already adopted these technologies. The use of AI in these medical institutions is still in its early stages, but it points out that the implementation of AI-based services, as well as the use of advanced technologies such as lifelogging (continuous health data monitoring), is in the planning stages.

However, for this to become a reality, continued efforts are needed to improve the quality of available data and develop new approaches to validate AI models in clinical settings. Collaboration between researchers, AI developers, and healthcare professionals will be essential to ensure that these technologies can be implemented safely and effectively.

AI is particularly effective in hospital settings, where it was applied in 60% of studies, generating improvements in both diagnosis and clinical management. For example, in a hospital setting, the study by (Valêncio et al., 2022) demonstrated that the use of AI for semi-automatic collection of data on stroke contributed to better patient monitoring and more assertive decision-making. These results are consistent with the literature that advocates the potential of AI to optimize hospital workflows, improve care efficiency, and reduce response time in critical diagnoses (Sariyar & Holm, 2022).

In the outpatient setting, which accounted for 30% of the studies, AI also played a relevant role, especially in areas such as telemedicine and dermatology. For example, (Jain et al., 2021) explored the use of AI in teledermatology practices to assist physicians and nurses in the assessment of dermatological conditions, resulting in more accurate diagnoses and a lower rate of need for biopsies. These results reinforce the hypothesis that AI can reduce the burden on healthcare professionals in outpatient settings, offering effective support and improving the quality of care. However, the study also revealed some limitations, such as variability in human assessments, highlighting the importance of continuous supervision by clinical experts.

An important point of discussion is the trust and transparency in AI models. (Sariyar & Holm, 2022) Point out that the lack of explainability in "black box" models used in deep neural networks still generates distrust among healthcare professionals. This barrier limits the full adoption of AI in clinical settings, as professionals need greater clarity about the algorithms' decision-making processes to fully trust the predictions made by machines. This challenge has been identified in several reviewed studies, suggesting that, to maximize the impact of AI in medicine, developers must invest in explainable AI (XAI), as proposed by (Carrasco-Ribelles et al., 2023).

It is observed that the analysis of the medical areas studied reveals that oncology and cardiology are the ones that benefit the most from AI, representing 35% and 25% of the studies, respectively. (Ladyzynski et al., 2022) Demonstrate the effectiveness of AI in predicting responses to cancer treatment, while (Valêncio et al., 2022) highlight the role of AI in monitoring cardiology patients in hospital settings. These empirical results support the theory that AI has greater applicability in areas that require high diagnostic accuracy and that deal with highly complex diseases, such as cancer and heart disease.

The data analysis also shows that AI has significant potential to transform medical practice, especially in hospital and outpatient settings, contributing to more accurate diagnoses and more informed clinical decisions. However, the challenges related to the transparency and reliability of AI models, as discussed in (Kueper et al., 2022), still need to be overcome for these technologies to be fully adopted in health systems.

CONCLUSIONS

The results obtained throughout this literature review confirm that AI has played a fundamental role in the evolution of medical practice, especially in the personalization of treatments and diagnostic accuracy. By reviewing 57 studies on AI applied to healthcare, it was possible to identify that the methodologies employed, such as machine learning and deep learning, have proven to be highly effective in hospital and outpatient settings, particularly in highly complex areas such as oncology and cardiology.

However, some challenges were identified, mainly related to the explainability of AI models, which continue to be a barrier to the full adoption of these technologies by healthcare professionals. The lack of transparency in "black box" algorithms generates distrust, limiting large-scale implementation, which points to the need for greater investment in explainable AI. Another difficulty observed was the variation in the quality and standardization of clinical data, which can affect the performance of predictive models, as highlighted by (Valêncio et al., 2022) and (Sariyar & Holm, 2022).

Finally, it is suggested that strategies be investigated to improve the transparency of AI algorithms, as well as the development of techniques to guarantee the quality of data used in predictive systems. Furthermore, it would be relevant to explore the impact of AI in less studied areas, such as psychiatry and pediatrics, where the potential for transformation may be equally significant. The adoption of AI in public health and its application in regions with less access to advanced technologies are also areas that deserve greater attention, as they can contribute to the democratization of medical care and equity in care.

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