INTERNATIONAL SEVEN JOURNAL OF MULTIDISCIPLINARY
ISSN: 2764-9547

ENVIRONMENTAL IMPACT OF THE USE OF ARTIFICIAL INTELLIGENCE IN HEALTH

https://doi.org/10.56238/isevmjv4n1-007

Recebimento dos originais: 14/12/2024 **Aceitação para publicação:** 14/01/2025

Rafael Dias Ribeiro[1], Amanda Gomes[2], Daniela Gomes[3], Gabriela Gomes[4], Erick Vitor de Souza[5], Renata de Carvalho Vieira Sousa[6], Valter Gomes[7] and Lucia Helena Gomes[8]

ABSTRACT

Artificial intelligence (AI) has emerged as a tool for innovation in healthcare, redefining diagnosis, treatment, and hospital management. From algorithms that improve medical image analysis to clinical decision support systems, AI offers significant benefits in the efficiency and accuracy of healthcare services. However, the growing demand for AI requires computing infrastructure, supported by data centers that consume large amounts of energy and natural resources. These centers, responsible for training and operating models such as GPT-3, generate significant greenhouse gas emissions and require large volumes of water for cooling. In addition, the production of specialized hardware and the disposal of equipment intensify environmental challenges. Paradoxically, AI also offers solutions to climate problems, such as optimizing energy resources and predicting natural disasters. The objective of this manuscript is to explore this duality, analyzing the benefits of AI in healthcare and the environmental challenges. Furthermore, sustainable practices and emerging technologies seek a balance between technological advancement and environmental preservation.

Keywords: Artificial Intelligence in Healthcare. Environmental Impact. Sustainable Technology.

[1] E-mail:rafaeldiaribeiro@gmail.com
ORCID: https://orcid.org/0009-0007-6105-8117
[2] E-mail: amandaggomes0@gmail.com
ORCID: https://orcid.org/0000-0003-0174-4856
[3] E-mail: gomesdaniela170@gmail.com
ORCID: https://orcid.org/0009-0005-0884-5168
[4] E-mail: gabrielaaggomes@gmail.com
ORCID: https://orcid.org/ 0000-0002-1008-1639
[5] E-mail: erickvitor72@hotmail.com
ORCID: https://orcid.org/0009-0007-8405-3271
[6] E-mail: renatadecarvalhov@gmail.com
ORCID: https://orcid .org/0009-0007-0055-4213
[7] E-mail: valtervieira@ufv.br
ORCID: https://orcid.org/0000-0002-8425-5355
[8] E-mail: lucia.gomes@ufv.br

INTRODUCTION

Artificial intelligence (AI) has established itself as an essential tool in the healthcare sector, improving diagnoses, treatments, and management processes. Its use ranges from advanced algorithms for analyzing medical images to clinical decision support systems, promoting greater efficiency and precision in healthcare services (MARTINEAU, 2020). However, despite technological advances, the application of AI also raises important environmental issues.

AI has revolutionized the healthcare sector, enabling more accurate analysis of medical data and promoting advances in personalized diagnoses and treatments (MARTINEAU, 2020). Models such as GPT-3 have been used to accelerate the analysis of large volumes of data, contributing to efficient hospital management. In addition, AI has demonstrated the potential to support telemedicine and predict epidemics, positively impacting access to healthcare in remote regions (ARBIX, 2024).

Training and operating AI models require robust computing infrastructures, often supported by data centers that consume large volumes of energy and natural resources. In addition to generating significant greenhouse gas emissions, these centers also have a significant impact on water resources, with it being estimated that training large models, such as GPT-3, can consume millions of liters of clean water for cooling (LI et al., 2023). The location and energy source used by these centers directly influences the carbon footprint of AI, highlighting the need for more sustainable practices (ARBIX, 2024).

Reviewed studies, such as that by (Li et al., 2023), highlight that training large AI models requires high energy and water consumption, due to the data center infrastructure. These centers can consume millions of liters of water and generate substantial carbon emissions, especially in places where energy is predominantly non-renewable. MIT reports (MARTINEAU, 2020) also highlight the role of materials used in hardware manufacturing, which intensifies environmental and social impacts due to mineral extraction production chains.

In addition, environmental impacts are not limited to energy consumption. The production and disposal of specialized hardware increases the extraction of materials and generates waste that contributes to environmental degradation and human rights violations in production chains (ARBIX, 2024). Paradoxically, AI also presents itself as an ally in the fight against climate change, being applied to optimize energy systems, predict environmental disasters, and implement more sustainable supply chains (ECYCLE, 2024).

The duality between the benefits and environmental impacts of AI is discussed in reports and articles reviewed in this study. Publications from the University of Berkeley and the journal Nature Climate Change reinforce the need for strategies such as the sustainable location of data centers, the adoption of renewable energy sources, and the optimization of computational processes to reduce the environmental footprint (ECYCLE, 2024).

Artificial intelligence (AI) has significantly transformed the healthcare sector, offering innovative solutions for diagnostics, treatments, and management of medical systems. However, the environmental impact associated with its development and application has raised concerns, prompting discussions about the need for sustainable practices. This study is based on a literature review that considers both the benefits and environmental challenges of AI, based on data according to relevance and reliability criteria.

Given this scenario, this article analyzes the use and benefits of AI in the healthcare sector, with a critical approach to environmental challenges. Based on a review of the impacts and existing solutions, we seek to propose paths that reconcile technological advancement with environmental preservation, promoting a sustainable future for the healthcare sector.

METHODOLOGY

This study uses an exploratory and descriptive approach to investigate and evaluate the impacts of artificial intelligence (AI) on health, with an emphasis on its environmental benefits and implications. The literature review was conducted in two main stages.

A combination of articles in scientific journals such as Nature, MIT News, and academic publications in arXiv were used. The search strategy was based on the following keywords: (("Artificial Intelligence" AND "Health") OR ("Environmental Impact" AND "Sustainable Technology") OR (“Artificial Intelligence” AND "Environmental Impact") OR (“Artificial Intelligence” AND "Sustainable Technology")). Inclusion criteria were established: articles in English, published between 2018-2023. Exclusion criteria: duplicate studies, abstracts, review articles, and works without access to the full text.

After data collection, the analysis will be structured in two stages. First, the articles were organized into categories related to the benefits of AI in health and environmental challenges, including energy consumption, water footprint, and impacts related to hardware production. In the second, an integrative analysis was carried out based on the reviewed literature, critical analysis of the data, discussing the duality between the technological benefits of AI and its environmental impacts. Furthermore, the review is limited to the literature and the relevance of the sources used. The proposal of the manuscript is a dialogue with an emphasis on sustainable practices in the use of AI in health.

RESULTS AND DISCUSSION

Artificial intelligence (AI) has proven to be an indispensable resource in the health area, promoting significant advances in diagnostics, treatments, and hospital management. The positive impact of AI is evident, but it is necessary to discuss how these advances influence the environment, considering the ecological footprint associated with its development and use.

CONTRIBUTIONS OF AI TO HEALTH

The analysis of the collected data demonstrates that AI plays a central role in the transformation of 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 the data and make predictions based on these 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 texts 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 the generated data from the 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 chronic lymphocytic leukemia (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 for how decisions or predictions were made. In the healthcare sector, this is crucial to increasing clinicians’ confidence in the predictions made by algorithms (Sariyar & Holm, 2022).

In (Clement & Maldonado, 2021), study presents the use of AI to aid clinical decision-making 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, and suggests 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 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 health care. 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 ongoing oversight of the models.

Khoury et al., 2022, emphasize that a framework is needed to evaluate, approve, and monitor the impact of these technologies. They highlight the importance of active participation by experts in the development, validation, and implementation of AI systems in the field of allergy and immunology, and discuss 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 OF THE STUDY

Although AI presents 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 the quantity and quality of data to provide accurate predictions (Akay et al., 2023) and (Bajgain et al., 2023) complement the need for a review focusing 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 the validity and challenges of clinical translation.

Heterogeneity in data collection methods and reporting practices are highlighted as important obstacles to overcome for effective implementation. In addition, 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. It suggests that the use of medical record assistants may isolate healthcare professionals from the continuous learning that occurs with AI integrated into EHRs, 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.

(Lim et al., 2022) explores the opinions of 603 patients on the use of artificial intelligence (AI) in the diagnosis of skin cancer. The survey revealed that 47% of participants were not opposed to the use of AI to assist skin specialists in diagnosis. However, 81% considered it 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 supportive tool, interaction with the clinician 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 of 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 about 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 healthcare 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 healthcare 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. While the benefits are clear, the environmental impact of the use of AI is worth highlighting. The need to train and operate large models, such as GPT-3 and GPT-4, demands significant computational infrastructure, supported by data centers that are highly energy and resource-intensive. It is estimated that GPT-3 training consumes up to 700,000 liters of clean water and a substantial amount of electricity, the carbon footprint of which varies depending on the energy mix of the location (LI et al., 2023).

Data centers used by major technology companies such as Google, Microsoft, and Amazon can dramatically increase CO_2 emissions depending on their locations and energy sources. In regions that rely on fossil fuels, these emissions become even more concerning. Reports indicate that AI’s carbon footprint is already equivalent to about 2% of global emissions, with a growing trend due to the increased demand for intensive computing (ARBIX, 2024; ECYCLE, 2024).

In addition, the environmental impact is also associated with the production of specialized hardware. The extraction of rare minerals and the manufacturing of components require high energy investments, often associated with environmental degradation and human rights issues. These challenges place sustainability as a central theme in the debate on the use of AI in health.

There are promising strategies to reduce the environmental impacts of AI without compromising its benefits in the health sector. The adoption of renewable energy sources to power data centers is a viable solution and is widely discussed in the literature (MARTINEAU, 2020). In addition, locating these centers in cold climate regions can reduce the need for intensive cooling and, consequently, energy and water consumption (LI et al., 2023).

Improving the energy efficiency of hardware and developing AI models that are less dependent on computational resources are also important strategies. Furthermore, transparency in the monitoring and disclosure of environmental data, such as carbon and water footprints, can drive public policies and investments in cleaner technologies.

Although AI offers unique opportunities to optimize health systems, it is essential to consider its environmental costs. The implementation of sustainable practices and green technologies in the health sector, such as the use of AI to predict and mitigate environmental impacts, can balance this duality. Thus, health and sustainability can go hand in hand, promoting a future where technological innovation does not compromise the environment, but, on the contrary, contributes to its preservation.

FINAL CONSIDERATIONS

Artificial intelligence (AI) has been consolidating itself as a tool in the health sector, bringing significant advances in diagnostics, treatments, and hospital management. The accurate and rapid analysis of data has transformed medical practice and the quality of care. However, as these technologies gain prominence, concerns about their environmental impacts emerge.

The analysis carried out in this study revealed an inherent duality in the application of AI in health. On the one hand, direct benefits, such as the optimization of medical resources and the personalization of treatments, contribute to a more efficient and accessible healthcare system. On the other hand, the high energy and water consumption for training and operating AI models, in addition to the environmental impacts associated with hardware production, present considerable challenges.

It is essential to adopt sustainable strategies that balance technological benefits with environmental preservation. Strategically locating data centers in regions with cold climates and renewable energy sources is one of the most promising solutions. In addition, the development of more efficient computing technologies, such as low-energy hardware and less resource-intensive AI models, can significantly reduce the carbon and water footprint.

REFERENCES

1. Adler-Milstein, J., Chen, J. H., & Dhaliwal, G. (2021). Next-generation artificial intelligence for diagnosis: From predicting diagnostic labels to "wayfinding". JAMA, 326(24), 2467–2468. https://doi.org/10.1001/jama.2021.22396

2. Akay, E. M. Z., Hilbert, A., Carlisle, B. G., Madai, V. I., Mutke, M. A., & Frey, D. (2023). Artificial intelligence for clinical decision support in acute ischemic stroke: A systematic review. Stroke, 54(6), 1505–1516. https://doi.org/10.1161/STROKEAHA.122.041442

3. Arbix, G. (2024). Como a rápida explosão de ferramentas de IA afeta o clima? Rádio USP. https://jornal.usp.br/?p=802425 (Acesso em: 16 de novembro de 2024)

4. Bajgain, B., Lorenzetti, D., Lee, J., & Sauro, K. (2023). Determinants of implementing artificial intelligence-based clinical decision support tools in healthcare: A scoping review protocol. BMJ Open, 13(2), e068373. https://doi.org/10.1136/bmjopen-2022-068373

5. Basit, M. A., Lehmann, C. U., & Medford, R. J. (2021). Managing pandemics with health informatics: Successes and challenges. Yearbook of Medical Informatics, 30(1), 17–25. https://doi.org/10.1055/s-0041-1726478

6. Carrasco-Ribelles, L. A., Llanes-Jurado, J., Gallego-Moll, C., Cabrera-Bean, M., Monteagudo-Zaragoza, M., Violán, C., & Zabaleta-Del-Olmo, E. (2023). Prediction models using artificial intelligence and longitudinal data from electronic health records: A systematic methodological review. Journal of the American Medical Informatics Association, 30(12), 2072–2082. https://doi.org/10.1093/jamia/ocad168

7. Clement, J., & Maldonado, A. Q. (2021). Augmenting the transplant team with artificial intelligence: Toward meaningful AI use in solid organ transplant. Frontiers in Immunology, 12, 694222. https://doi.org/10.3389/fimmu.2021.694222

8. Dobson, R., Wihongi, H., & Whittaker, R. (2023). Exploring patient perspectives on the secondary use of their personal health information: An interview study. BMC Medical Informatics and Decision Making, 23(1), 66. https://doi.org/10.1186/s12911-023-02143-1

9. Ecycle. (2024). Pegada de carbono da inteligência artificial. eCycle. https://www.ecycle.com.br/pegada-de-carbono-da-inteligencia-artificial/ (Acesso em: 16 de novembro de 2024)

10. Gellert, G. A. (2023). Medical scribes: Symptom or cause of impeded evolution of a transformative artificial intelligence in the electronic health record? Perspectives in Health Information Management, 20(1), 1d. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9860472

11. Jain, A., Way, D., Gupta, V., Gao, Y., de Oliveira Marinho, G., Hartford, J., Sayres, R., Kanada, K., Eng, C., Nagpal, K., DeSalvo, K. B., Corrado, G. S., Peng, L., Webster, D. R., Dunn, R. C., Coz, D., Huang, S. J., Liu, Y., Bui, P., & Liu, Y. (2021).

Development and assessment of an artificial intelligence-based tool for skin condition diagnosis by primary care physicians and nurse practitioners in teledermatology practices. JAMA Network Open, 4(4), e217249. https://doi.org/10.1001/jamanetworkopen.2021.7249

12. Jeong, H., & Kamaleswaran, R. (2022). Pivotal challenges in artificial intelligence and machine learning applications for neonatal care. Seminars in Fetal and Neonatal Medicine, 27(5), 101393. https://doi.org/10.1016/j.siny.2022.101393

13. Kashyap, S., Morse, K. E., Patel, B., & Shah, N. H. (2021). A survey of extant organizational and computational setups for deploying predictive models in health systems. Journal of the American Medical Informatics Association, 28(11), 2445–2450. https://doi.org/10.1093/jamia/ocab154

14. Kenner, B. J., Abrams, N. D., Chari, S. T., Field, B. F., Goldberg, A. E., Hoos, W. A., Klimstra, D. S., Rothschild, L. J., Srivastava, S., Young, M. R., & Go, V. L. W. (2021). Early detection of pancreatic cancer: Applying artificial intelligence to electronic health records. Pancreas, 50(7), 916–922. https://doi.org/10.1097/MPA.0000000000001882

15. Khoury, P., Srinivasan, R., Kakumanu, S., Ochoa, S., Keswani, A., Sparks, R., & Rider, N. L. (2022). A framework for augmented intelligence in allergy and immunology practice and research: Work group report of the AAAAI Health Informatics, Technology, and Education Committee. Journal of Allergy and Clinical Immunology: In Practice, 10(5), 1178–1188. https://doi.org/10.1016/j.jaip.2022.01.047

16. Kulkarni, P. A., & Singh, H. (2023). Artificial intelligence in clinical diagnosis: Opportunities, challenges, and hype. JAMA, 330(4), 317–318. https://doi.org/10.1001/jama.2023.11440

17. Ladyzynski, P., Molik, M., & Foltynski, P. (2022). Dynamic Bayesian networks for prediction of health status and treatment effect in patients with chronic lymphocytic leukemia. Scientific Reports, 12(1), 1811. https://doi.org/10.1038/s41598-022-05813-8

18. Letterie, G. (2021). Three ways of knowing: The integration of clinical expertise, evidence-based medicine, and artificial intelligence in assisted reproductive technologies. Journal of Assisted Reproduction and Genetics, 38(7), 1617–1625. https://doi.org/10.1007/s10815-021-02159-4

19. Li, P., Yang, J., Islam, M. A., & Ren, S. (2023). Tornando a IA menos “sedenta”: Descobrindo e abordando a pegada hídrica secreta dos modelos de IA. arXiv. https://arxiv.org/abs/2304.03271 (Acesso em: 16 de novembro de 2024)

20. Martineau, K. (2020). Reduzindo a pegada de carbono do aprendizado profundo. MIT News. https://news.mit.edu/2020/shrinking-deep-learning-carbon-footprint-0807 (Acesso em: 16 de novembro de 2024)

21. Mattay, G. S., Griffey, R. T., Narra, V., Poirier, R. F., & Bierhals, A. (2023). Impact of predictive text clinical decision support on imaging order entry in the emergency department. Journal of the American College of Radiology, 20(12), 1250–1257. https://doi.org/10.1016/j.jacr.2023.05.023

22. Maurovich-Horvat, P. (2021). Current trends in the use of machine learning for diagnostics and/or risk stratification in cardiovascular disease. Cardiovasc Res, 117(5), e67–e69. https://doi.org/10.1093/cvr/cvab059

23. Maurud, S., Henni, S. H., & Moen, A. (2023). Health Equity in Clinical Research Informatics. Yearb Med Inform, 32(1), 138–145. https://doi.org/10.1055/s-0043-1768720

24. Mendo, I. R., Marques, G., de la Torre Díez, I., López-Coronado, M., & Martín-Rodríguez, F. (2021). Machine Learning in Medical Emergencies: a Systematic Review and Analysis. J Med Syst, 45(10), 88. https://doi.org/10.1007/s10916-021-01762-3

25. Mohsen, F., Ali, H., El Hajj, N., & Shah, Z. (2022). Artificial intelligence-based methods for fusion of electronic health records and imaging data. Sci Rep, 12(1), 17981. https://doi.org/10.1038/s41598-022-22514-4

26. Montanaro, V. V. A., et al. (2021). Artificial Intelligence-Based Decision for the Prediction of Cardioembolism in Patients with Chagas Disease and Ischemic Stroke. J Stroke Cerebrovasc Dis, 30(10), 106034. https://doi.org/10.1016/j.jstrokecerebrovasdis.2021.106034

27. Morey, J. R., et al. (2021). Real-world experience with Artificial Intelligence-Based Triage in Transferred Large Vessel Occlusion Stroke Patients. Cerebrovasc Dis, 50(4), 450–455. https://doi.org/10.1159/000515320

28. Morin, O., et al. (2021). An artificial intelligence framework integrating longitudinal electronic health records with real-world data enables continuous pan-cancer prognostication. Nat Cancer, 2(7), 709–722. https://doi.org/10.1038/s43018-021-00236-2

29. Reeves, J. J., et al. (2021). The Clinical Information Systems Response to the COVID-19 Pandemic. Yearb Med Inform, 30(1), 105–125. https://doi.org/10.1055/s-0041-1726513

30. Ren, Y., et al. (2022). Performance of a Machine Learning Algorithm Using Electronic Health Record Data to Predict Postoperative Complications and Report on a Mobile Platform. JAMA Netw Open, 5(5), e2211973. https://doi.org/10.1001/jamanetworkopen.2022.11973

31. Riskin, D., et al. (2023). Using artificial intelligence to identify patients with migraine and associated symptoms and conditions within electronic health records. BMC Med Inform Decis Mak, 23(1), 121. https://doi.org/10.1186/s12911-023-02190-8

32. Rodriguez-Diaz, E., et al. (2022). Artificial Intelligence-Based Assessment of Colorectal Polyp Histology by Elastic-Scattering Spectroscopy. Dig Dis Sci, 67(2), 613–621. https://doi.org/10.1007/s10620-021-06901-x

33. Rostam Niakan Kalhori, S., et al. (2021). Enhanced childhood diseases treatment using computational models: Systematic review of intelligent experiments heading to precision medicine. J Biomed Inform, 115, 103687. https://doi.org/10.1016/j.jbi.2021.103687

34. Sagheb, E., et al. (2022). Artificial Intelligence Assesses Clinicians' Adherence to Asthma Guidelines Using Electronic Health Records. J Allergy Clin Immunol Pract, 10(4), 1047–1056.e1. https://doi.org/10.1016/j.jaip.2021.11.004

35. Samaran, R., et al. (2021). Interest in artificial intelligence for the diagnosis of non-melanoma skin cancer: a survey among French general practitioners. Eur J Dermatol, 31(4), 457–462. https://doi.org/10.1684/ejd.2021.4090

36. Samaras, A., et al. (2023). Artificial intelligence-based mining of electronic health record data to accelerate the digital transformation of the national cardiovascular ecosystem: design protocol of the CardioMining study. BMJ Open, 13(4), e068698. https://doi.org/10.1136/bmjopen-2022-068698

37. Sariyar, M., & Holm, J. (2022). Medical Informatics in a Tension Between Black-Box AI and Trust. Stud Health Technol Inform, 289, 41–44. https://doi.org/10.3233/SHTI210854

38. Shevchenko, E. V., et al. (2022). [Artificial intelligence guided predicting the length of hospital stay in a neurosurgical hospital based on the text data of electronic medical records]. Zh Vopr Neirokhir Im N N Burdenko, 86(6), 43–51. https://doi.org/10.17116/neiro20228606143

39. Strauss, A. T., et al. (2023). Artificial intelligence-based clinical decision support for liver transplant evaluation and considerations about fairness: A qualitative study. Hepatol Commun, 7(10). https://doi.org/10.1097/HC9.0000000000000239

40. Tashman, A. P. (2022). Practical Implementation and Challenges of Artificial Intelligence-Driven Electronic Health Record Evaluation: Protected Health Information. Adv Chronic Kidney Dis, 29(5), 427–430. https://doi.org/10.1053/j.ackd.2022.05.003

41. Wu, D. T. Y., et al. (2022). Development of a Clinical Decision Support System to Predict Unplanned Cancer Readmissions. AMIA Annu Symp Proc, 2022, 1173–1180. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10148334

42. Xu, Q., et al. (2023). Interpretability of Clinical Decision Support Systems Based on Artificial Intelligence from Technological and Medical Perspective: A Systematic Review. J Healthc Eng, 2023, 9919269. https://doi.org/10.1155/2023/9919269

43. Yao, X., et al. (2021). Batch enrollment for an artificial intelligence-guided intervention to lower neurologic events in patients with undiagnosed atrial fibrillation: rationale

and design of a digital clinical trial. Am Heart J, 239, 73–79. https://doi.org/10.1016/j.ahj.2021.05.006

44. Yun, H. J., et al. (2021). Adequacy and Effectiveness of Watson For Oncology in the Treatment of Thyroid Carcinoma. Front Endocrinol (Lausanne), 12, 585364. https://doi.org/10.3389/fendo.2021.585364

45. Zhou, Q., et al. (2021). A machine and human reader study on AI diagnosis model safety under attacks of adversarial images. Nat Commun, 12(1), 7281. https://doi.org/10.1038/s41467-021-27577-x

46. Zhu, Y., et al. (2022). Agitation Prevalence in People With Dementia in Australian Residential Aged Care Facilities: Findings From Machine Learning of Electronic Health Records. J Gerontol Nurs, 48(4), 57–64. https://doi.org/10.3928/00989134-20220309-01