IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 4, August 2026, pp. 3053~3067
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i4.pp3053-3067

Bridging gaps in health artificial intelligence: challenges in MDPI research articles

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Article Info

Article history:

Received Mar 23, 2025
Revised May 21, 2026
Accepted Jun 19, 2026

Keywords:

Artificial intelligence
Bibliometric analysis
Health
Research challenge
VOSviewer

ABSTRACT

Technological advancements in artificial intelligence (AI) have transformed healthcare by improving early disease detection, personalized treatment, predictive analytics, and clinical decision support systems. However, AI adoption in healthcare faces critical challenges, including data privacy concerns, algorithmic bias, regulatory barriers, usability issues, and system interoperability. Addressing these issues requires standardized regulations, ethical frameworks, and interdisciplinary collaboration to ensure responsible AI integration. This study systematically analyzes research trends in health AI over the past six years through a systematic literature review (SLR) and a bibliometric analysis using VOSviewer. The review focuses on Multidisciplinary Digital Publishing Institute (MDPI) journal articles to identify key contributors, emerging trends, and research gaps in AI-driven healthcare. Findings highlight dominant research areas, including machine learning for diagnosis, AI-driven hospital management, and predictive analytics, while exposing persistent challenges such as a lack of standardized AI models, ethical concerns, and accessibility disparities. By mapping the research landscape, this study provides evidence-based insights and recommendations to address AI adoption barriers, improve transparency, and guide future research in healthcare AI. The results contribute to developing a more equitable, efficient, and trustworthy AI-driven healthcare system.

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1. INTRODUCTION

Technological advancements continue to revolutionize various industries, with healthcare undergoing some of the most profound transformations. Innovations like telemedicine, wearable health devices, and electronic medical records have significantly improved patient care and streamlined operations. These advancements have paved the way for the integration of artificial intelligence (AI), which is redefining healthcare delivery and management.

AI has proven beneficial in enhancing clinical decision-making, optimizing hospital workflows, refining medical imaging, and transforming patient monitoring through AI-driven wearables [1]. Machine learning and data-driven approaches enable AI to analyze large medical datasets, leading to more accurate diagnostics and optimized treatment plans [2]. AI's impact is particularly evident in areas like early disease detection, personalized treatment, and clinical decision support, which improve precision and efficiency in healthcare delivery [1], [2]. Additionally, AI contributes to innovative healthcare solutions through biosensing, remote patient monitoring, and predictive analytics, demonstrating its broad applicability [3], [4].

Despite these advancements, integrating AI into healthcare presents persistent challenges. AI plays a critical role in infectious disease management, resource allocation, and public health crisis responses [5]. Its potential to optimize healthcare management—including process automation, resource distribution, and crisis preparedness—illustrates its transformative capability [6]. However, real-world implementation remains complex, particularly in emergency preparedness, where further research is required to evaluate AI's effectiveness [6]. Moreover, in countries like India, AI adoption faces hurdles due to infrastructure limitations, regulatory gaps, and a lack of awareness regarding AI ethics [7]. Recent studies indicate that AI implementation in healthcare is strongly influenced by organizational readiness, clinician trust, and governance structures. Healthcare providers often express concerns regarding workflow integration, transparency, and accountability of AI-driven systems, which significantly affect adoption rates [8], [9].

To systematically analyze research trends in healthcare AI, bibliometric methods provide valuable insights into existing literature and key areas of study. VOSviewer is a software tool for constructing and visualizing bibliometric networks, including journals, researchers, and publications, based on citation, bibliographic coupling, co-citation, and co-authorship relations [10]. This study employs bibliometric analysis to assess AI developments in healthcare using Multidisciplinary Digital Publishing Institute (MDPI) journal articles, mapping key trends, research gaps, and potential future directions.

However, beyond technical capabilities, AI adoption is influenced by workforce readiness and healthcare professionals' competency in integrating AI into clinical settings [11]. The perception of AI among medical personnel also plays a crucial role in adoption rates. Furthermore, disparities in access to AI-powered healthcare solutions remain a concern, especially in low-resource settings, which limit equitable healthcare distribution [12]. Ensuring compliance with ethical and regulatory standards, particularly in data security and model transparency, is crucial for widespread AI adoption in healthcare [7]. In addition, privacy-preserving techniques such as federated learning and secure multiparty computation have been proposed to mitigate data leakage risks and enhance compliance with data protection regulations in AI-enabled healthcare systems [13].

Empirical evidence demonstrates that algorithmic bias may lead to unequal diagnostic performance across demographic groups, thereby reinforcing existing health disparities if not properly addressed [14]. Another pressing issue is AI reliability, as model bias, prediction errors, and lack of standardization can undermine clinical decision-making and compromise patient safety [15]. Addressing algorithmic bias and fostering trust in AI models requires enhanced transparency and interpretability. Additionally, the successful integration of AI relies on system interoperability and user-friendly applications, as technical complexity often hinders adoption [11].

Beyond technical and operational challenges, AI faces governance, policy, and regulatory constraints. Ethical considerations, data privacy concerns, and legal requirements demand stringent compliance with healthcare regulations [16], [17]. The increasing sophistication of AI necessitates explainable and interpretable models to build trust among clinicians and patients. Explainable artificial intelligence (XAI) frameworks have been developed to enhance interpretability and strengthen clinician trust in AI-assisted decision-making processes [18], [19]. Without proper risk management frameworks, AI integration may introduce inefficiencies rather than enhance healthcare delivery [20].

Despite these obstacles, AI remains a transformative force in healthcare, improving patient outcomes, advancing pharmaceutical research, and optimizing resource management [19]. Addressing key challenges such as accessibility, usability, cross-sector collaboration, and regulatory concerns is essential to maximizing AI's impact. This study aims to bridge existing gaps by identifying unresolved issues and exploring insights from MDPI journal articles to guide future advancements in healthcare AI. Bibliometric analysis has been widely utilized to map research trends, identify thematic structures, and detect emerging topics in healthcare AI studies [21], [22]. Integrating bibliometric mapping with visualization tools enables a systematic and evidence-based exploration of evolving research landscapes. Previous bibliometric analyses of AI in healthcare have typically drawn on large databases such as ScienceDirect and Scopus [23]. In contrast, this study focuses exclusively on MDPI journal articles. This focus is scientifically valuable because MDPI's fully open-access model ensures that all full texts are freely available [24], enabling more in-depth text mining beyond abstract-only analyses. Moreover, MDPI's expansive portfolio (now over 500 journals [25]) and expedited editorial process (targeting publication within ≈ 5–7 weeks of submission [26]) create a large, up-to-date corpus, making it a sensitive barometer of emerging trends in the rapidly evolving field of health AI. Importantly, this MDPI-centric approach is intended to complement rather than replace broader bibliometric surveys by providing a detailed perspective on one influential open-access ecosystem. The present study analyzes MDPI health AI publications from 2019 to 2024.

2. METHOD

This section describes the methodological framework applied in this study to analyze research trends and challenges in health AI. The research design integrates a systematic literature review (SLR) with bibliometric analysis to ensure a structured, transparent, and reproducible investigation process. This combined approach enables systematic article selection, keyword mapping, and trend visualization based on clearly defined inclusion criteria and analytical procedures.

2.1. Methodology diagram

The methodology used for this paper can be seen in Figure 1 as a SLR based on [27]. According to Farooq *et al.* [27], the reason for following the methodology proposed by Kitchenham and Charters [28] is so that the selection of information and representation results to support the making of research is carried out impartially. For the steps carried out in this paper, we take 4 parts of the process from [27], namely, specify the research objective; define the research question (RQ); establish the search string; and select the keyword, as shown in Figure 1. Determine the research objective to be achieved. Next, determine the RQ and the main motivation for writing this article. Collect articles related to the research topic on one of the publishers, namely MDPI, by entering relevant search strings. Then, select the keywords that suit the analysis needs in this article. AI technology, such as ChatGPT, DeepSeek, and Claude AI, is also used as a tool that helps in the work of this article.

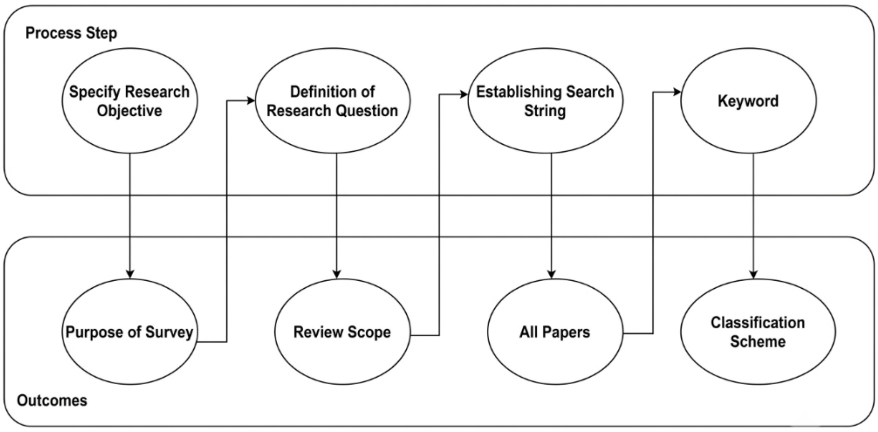

Figure 1. Method implementation

2.2. Research objectives

The purpose of this article is presented through two research objectives:
RO1: focused state-of-the-art research work has been identified in the field of health AI.
RO2: identify the research gaps in terms of challenges.

2.3. Research questions and main motivation

Table 1 displays the RQ and main motivation of this paper. To formulate the RQ and determine the main motivation of this paper, the help of one of the AI tools, ChatGPT, was utilized. These are presented in Table 1.

Table 1. RQ and main motivation

ID	RQ	Main motivation
RQ1	How do relationships between keywords in the health AI study relate to challenges in this field?	Identifying the relationship between keywords within keywords in the study of AI in health and challenges in this field using VOSviewer with network visualization helps to understand the interconnectedness of concepts and interconnected research fields.
RQ2	How has the development of research trends related to health AI over time?	Find out the development of Health AI challenges research trends over time using VOSviewer with overlay visualization, providing insight into how the research focus is changing and evolving.
RQ3	What are the most researched and still rarely explored research areas in keywords in the health AI study and Challenges in this field?	Identify the most researched topics as well as areas that are still rarely explored using VOSviewer with density visualization in keywords in the health AI study and challenges in this field, thus showing potential research gaps.

2.4. MDPI publisher

MDPI is a publisher of peer-reviewed, open-access journals known for its rigorous and fast editorial workflow [29]. Established in June 1996 by Dr. Shu-Kun Lin and Dr. Benoit R. Turin as a non-profit institute in Basel, MDPI later evolved into the present-day publishing house known as MDPI AG [30]. MDPI launched its first online journal, Molecules, in 1996 and has since positioned itself at the forefront of the open access movement, ensuring that high-quality research is quickly verified and made available to the community under a Creative Commons Attribution License. MDPI's publication scope covers a wide range of scientific disciplines, including biology, chemistry, engineering, medicine, social sciences, economics, and many other fields [29].

2.5. VOSViewer

VOSviewer is a software tool for constructing and visualizing bibliometric networks, including journals, researchers, and publications, based on citation, bibliographic coupling, co-citation, and co-authorship relations [10]. It also provides text mining functionality to construct and visualize co-occurrence networks of important terms extracted from scientific literature. Figure 2 shows the initial view of the VOS viewer interface. The guide to using VOSviewer can be accessed by clicking the "Manual" button on the left panel in the "info" section, which can be seen in Figure 2.

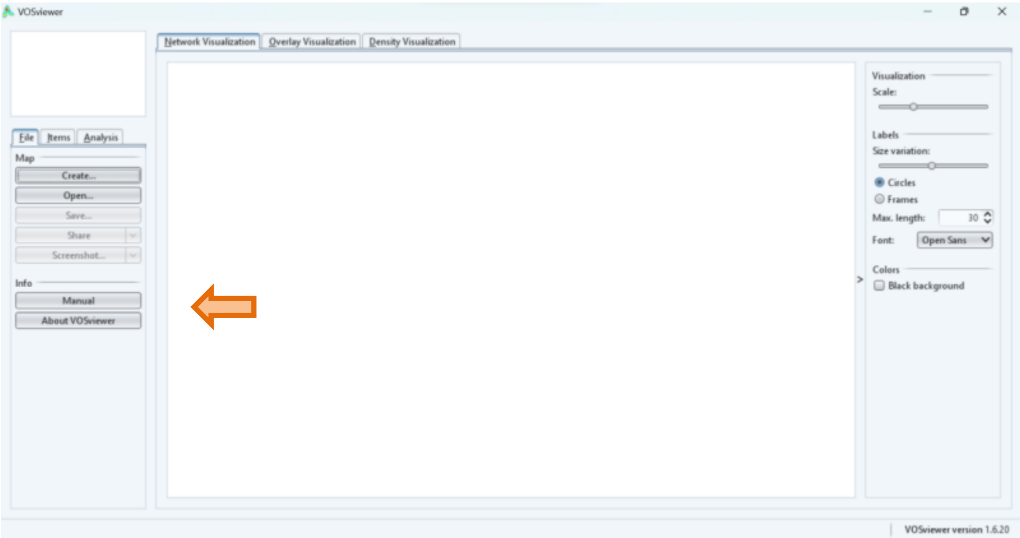

Figure 2. Initial of the VOSviewer interface

2.6. Keyword

This subsection describes the keyword selection and search strategy applied to retrieve relevant publications from the MDPI database. The keywords were defined to reflect the core focus of the study, which examines research trends and implementation challenges in health AI. By structuring the search terms around the concepts of health, AI, and challenges.

2.6.1. Search string

Determining the search string is used to collect published articles related to the research topic [6]. A search string is a combination of keywords, truncation symbols, and Boolean operators you enter into the search box of a library database or search engine [31]. Boolean operators are connector words that aim to combine or exclude words in a search string so that the resulting output becomes more focused, such as AND (displaying results that contain all entered terms), OR (displaying results that contain at least one entered term), NOT (displaying results that contain the first search term but excluding or not displaying search results that contain the second search term) [31], [32].

Table 2 shows the search string used in this article. This article uses 3 strings to search for relevant articles in MDPI, including "Health", "Artificial Intelligence", and "Challenge", and the Boolean operator used is AND. For the search type section, the one selected is "All fields". Figure 3 shows the implementation of the search string to MDPI using the "Advanced" feature.

Table 2. Search string

Source	Search string	Context
MDPI	(“Health”) AND (“Artificial Intelligence”) AND (“Challenge”)	Health Artificial Intelligence

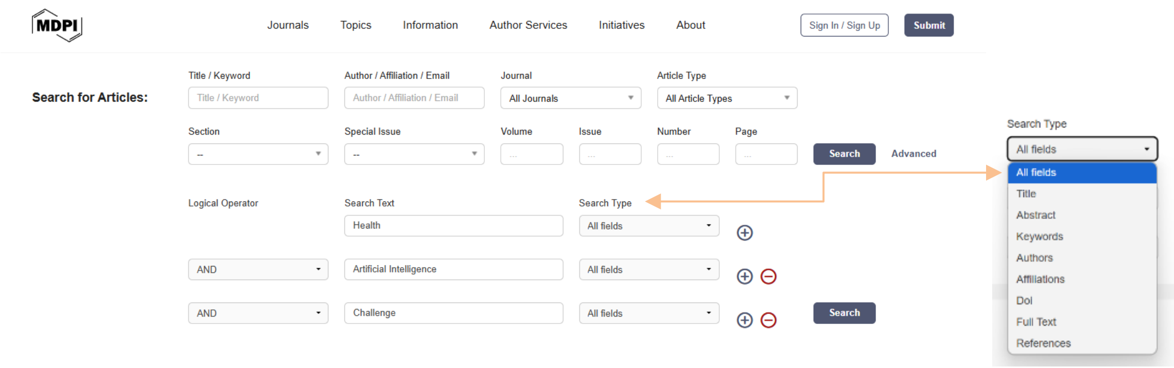

Figure 3. Applied the search string in MDPI

2.6.2. Inclusion and exclusion criteria

The study selection process followed a structured screening approach. Firstly, articles were retrieved using predefined keywords from the MDPI database. Subsequently, title and abstract screening were conducted to exclude irrelevant studies, followed by eligibility assessment. Only studies meeting all inclusion criteria were retained for bibliometric and SLR analysis, presented in Table 3.

Table 3. Criterion explanation

Type	Criterion	Rationale
Inclusion	Published between 2019 and 2024	To capture recent developments in health AI research
Inclusion	English-language articles	To ensure consistency in data extraction and analysis
Inclusion	Indexed in MDPI articles	To maintain dataset consistency
Inclusion	Relevant to health AI and challenges	To align with research objectives
Inclusion	Research and review articles	To include both empirical and synthesis studies
Exclusion	Conference abstracts	Often lack methodological completeness
Exclusion	Editorial, notes, book reviews	Non-empirical and limited analytical value
Exclusion	Irrelevant after title/abstract screening	To remove off-topic studies

2.6.3. Article selection and data export

Article selection was conducted through a systematic filtering process using the MDPI search engine to ensure relevance to health AI and challenges research. To operationalize this selection process, a set of specific search parameters was defined to narrow the scope and retrieve the most relevant publications. Table 4 shows the parameters applied to the MDPI search engine to focus the literature review process in the field of health AI at MDPI publishers.

Table 4. Applied parameters for the MDPI search engine

Parameters/filters	Value
Years	2019-2024
Subjects	Public health and healthcare
Journals	Healthcare
Articles type	Article

Table 4 presents the search parameters and filters applied in the MDPI database for conducting a literature review on AI in the health field. The time range for the search is defined from 2019 to 2024, ensuring the retrieval of the most recent and relevant studies that reflect advancements in health AI over the last six years. The subject selected is “Public health and healthcare”, emphasizing the interdisciplinary nature of health AI, which explains AI implementation in healthcare. The journals specifically targeted are healthcare, which is a prominent MDPI publication known for hosting peer-reviewed articles on healthcare technology. The article type filter is set to “Article”, focusing on original research contributions rather than reviews, editorials, or other content types. These filters collectively aim to streamline the search process, ensuring a focused, high-quality dataset of relevant publications for a comprehensive review in the health AI field. Figure 4 shows the implementation of the search filter to MDPI.

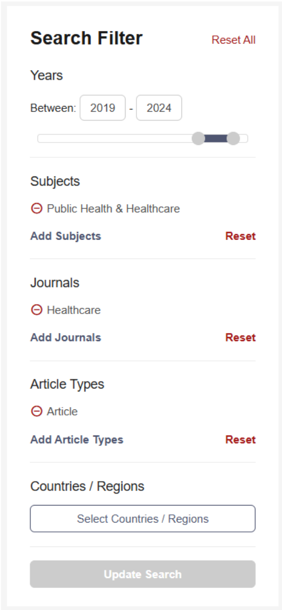

Figure 4. Applied search filter in MDPI

Data used in this study uses exported Research Information Systems (RIS) formatted data from articles published on MDPI. Figure 5 shows how to export data using the RIS format. After successfully applying the search string and performing a search filter according to the analysis needs in this article, select "Time cited" in the order results, "Normal" in the result details, and select "200" articles displayed per page of the website. Next, click "Show export options", then select "RIS", then check the box on "Select all" to select all the journals to export data, and then click the "export" button. This is done for each website page that displays a maximum of 200 articles until the last page.

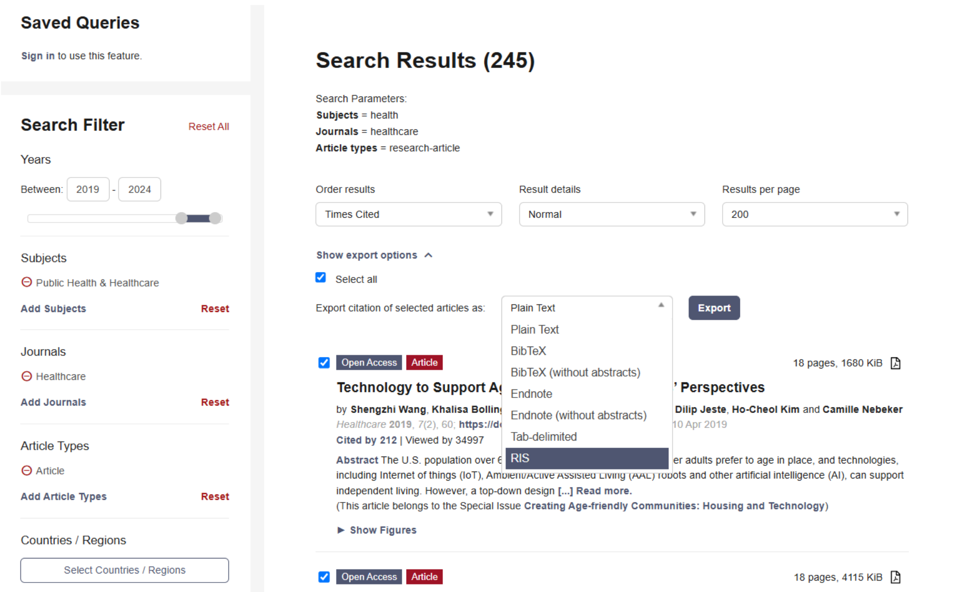

Figure 5. Export data using the RIS format in MDPI

3. RESULTS AND DISCUSSION

Based on the search results of the articles with keywords health, AI, and challenge in 2019-2024 (6 years), there are 245 articles obtained. The exported data was then visualized with VOSviewer to view the relation of authorship, the relation of keywords, as well as the research trend of related topics in health AI between 2019 and 2024. Table 5 explains the trend in the number of articles published in the field of health AI from 2019 to 2024, specifically, those that also have the word "challenge" based on the search string results applied, totaling 245 publications. In 2019, there were 2 publication articles, then increased in 2020 with 12 publication articles, then experienced a significant enough increase in 2021 with 44 publication articles, then also increased in 2022 with 68 publication articles, but there was a decrease in 2023 with 66 publication articles and decreased again in 2024 with 53 publication articles.

Table 5. Number of published articles from 2019 to 2024

Year	Number of articles
2019	2
2020	12
2021	44
2022	68
2023	66
2024	53
Total published articles	245

Table 6 explains article citation data from 2019 to 2024 with the topic of health AI articles based on the search string results applied, which have received significant attention. This result is obtained by using "Time cited" for the order results section and 10 for results per page on the first page in MDPI. An article by Wang *et al*. [33] leads with 212 citations, followed the article by Reshan *et al*. [34] with 138 citations, and the article by Battineni *et al*. [35] with 105 citations. Other articles, such as [36]–[42] also included in the top 10 articles with the highest number of citations. This distribution of highly-cited articles demonstrates that health AI research during this period was largely driven by pandemic response needs and technological advances in deep learning for diagnostic applications.

Table 6. Authors with the most citations

Authors	Number of citations
Wang *et al.* [33]	212
Reshan *et al.* [34]	138
Battineni *et al.* [35]	105
Khanna *et al.* [36]	92
Temsah *et al.* [37]	76
Ahsan *et al.* [38]	73
Almalki *et al.* [39]	72
Amou *et al.* [40]	68
Tran *et al.* [41]	65
Alwakid *et al.* [42]	63

3.1. Network visualization

The collaborative structure among authors in the health AI field, with distinct color-coded clusters representing groups of researchers frequently co-authoring publications together illustrated in Figure 6. There are 218 clusters based on the results from VOSviewer, among which the densely connected red cluster represents a large established community, while the green, blue, yellow, purple, turquoise, and orange clusters constitute substantial secondary research groups, and the grey clusters represent numerous smaller research communities, each comprising fewer than 20 authors. The visualization emphasizes the formation of clusters based on co-authorship frequency, with most collaborations occurring within large clusters representing broader collaborative efforts. The red cluster, positioned separately on the right side of the network, appears as one of the largest and most densely connected groups, suggesting a highly productive but relatively self-contained collaboration community with limited external partnerships. Additional major clusters, including the green, blue, and yellow groups, also exhibit dense co-authorship ties, likely reflecting sustained collaboration patterns shaped by shared institutional affiliations, geographic proximity, or common research interests. In contrast, the large concentration of grey nodes in the central region represents a broader background network of authors with weaker collaboration intensity, smaller publication footprints, and less consolidated cluster membership. Overall, the relatively sparse inter-cluster connections and limited number of bridging authors suggest that while strong local collaboration exists within individual research communities, broader cross-cluster and cross-institutional collaboration remains weak. This fragmented collaboration landscape may restrict interdisciplinary knowledge exchange and integration, highlighting the need for stronger international and cross-disciplinary partnerships to advance innovation in health AI research.

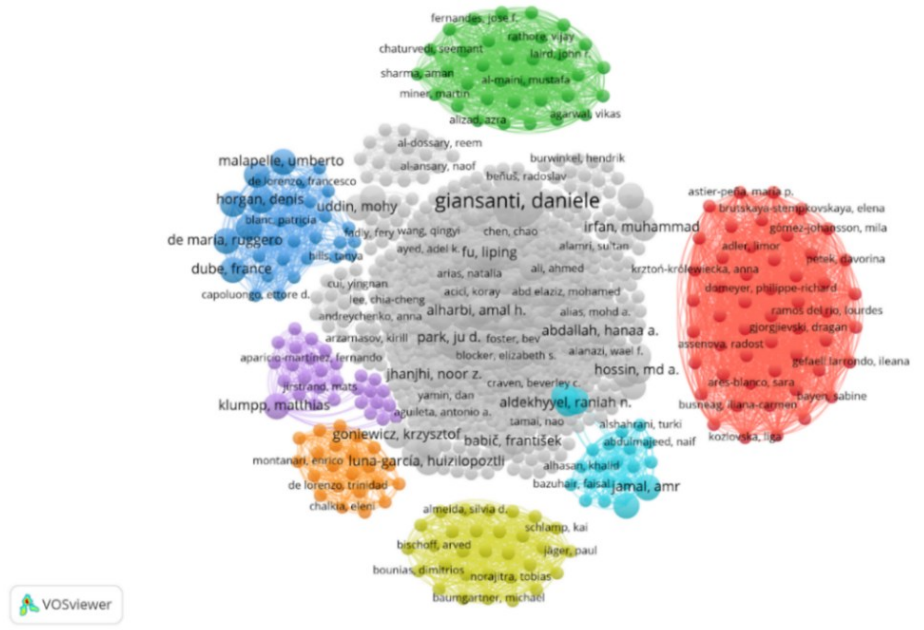

Figure 6. Co-authorship network visualization

Table 7 provides a quantitative breakdown of the largest clusters identified in the co-authorship network visualization in Figure 6, illustrating the distribution of author collaborations in the health AI field. The largest cluster is the red cluster, consisting of 51 authors, followed by the green cluster with 35 authors and the blue cluster with 30 authors, confirming that the most intensive research collaborations occur within these large groups. Meanwhile, the remaining 211 clusters (clusters 8 through 218) are colored grey, and each consists of fewer than 20 authors, indicating the presence of numerous small research teams or more limited researcher communities within the overall collaboration network.

Table 7. Clusters with the most authors

Cluster	Number of authors	Cluster color
1	51	Red
2	35	Green
3	30	Blue
4	30	Yellow
5	29	Purple
6	22	Turquoise
7	22	Orange
8-218	Less than 20 (1 to 19)	Grey

Figure 7 illustrates the relationships and co-occurrences among key terms in the health AI research field, with nodes representing keywords and edges showing the strength of their connections. Larger nodes indicate more frequently used keywords, while the proximity and thickness of edges reflect the closeness and frequency of their co-occurrence. Although “COVID-19” appears as one of the largest and most prominent nodes, indicating its high frequency and importance in the dataset, the network is conceptually centered around “artificial intelligence” and “machine learning”, which occupy more central positions and display extensive connections with multiple clusters. This suggests that while COVID-19 served as a major application domain between 2019 and 2024, AI and machine learning functioned as the primary methodological backbone of the literature. The red cluster represents the core methodological foundation of AI in healthcare, centered on “artificial intelligence” and “machine learning”, with associated terms such as “electronic health records”, “prediction”, and “diagnosis”. The dense internal connectivity of the cluster indicates the strong integration of predictive and diagnostic clinical data processing, highlighting the widespread use of machine learning techniques for healthcare decision support and disease prediction. The green cluster focuses on deep learning applications in medical imaging and diagnostic classification, anchored by the node “deep learning” and connected to terms such as “x-ray”, “pneumonia”, and “explainable AI classification”. The proximity among these nodes suggests a highly specialized and technically cohesive research area centered on automated image analysis and radiological diagnosis. The yellow cluster is organized around “COVID-19” and captures pandemic-driven healthcare applications, including “telemedicine”, “mental health”, “radiology”, and “forecasting”. The prominence of this cluster reflects the acceleration of AI adoption during the pandemic, particularly for remote healthcare delivery, outbreak prediction, and pandemic-related clinical management. Overall, the visualization demonstrates that current healthcare AI research is dominated by methodological AI development and pandemic-related applications, while emerging themes such as XAI and ethical digital health implementation remain relatively peripheral. These peripheral yet growing clusters suggest important future research opportunities, particularly in integrating AI innovations with human-centered healthcare applications, as concluded in Table 8.

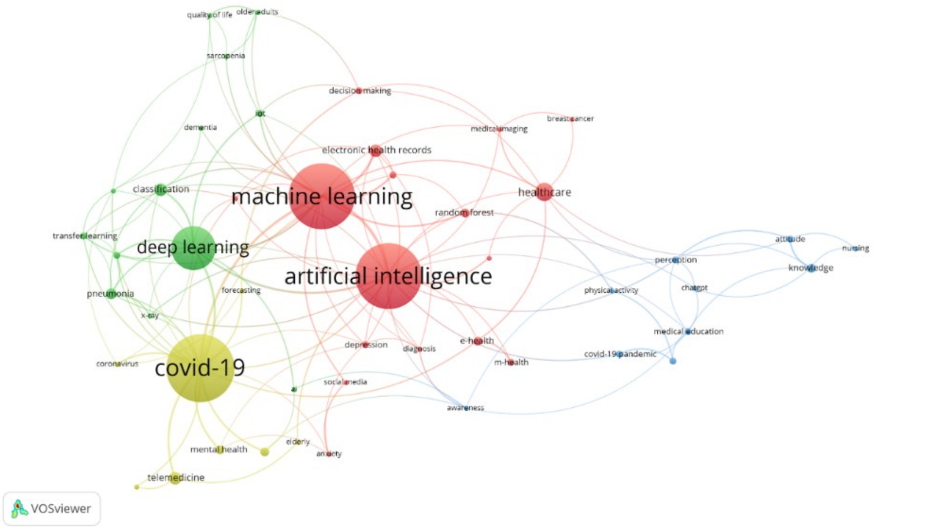

Figure 7. Keyword relationship and co-occurrence visualization

Table 8. Keyword clusters with the most occurrences

Cluster	Color	Keyword	Occurrences	Links	Total link strengths (TLS)
1	Yellow	COVID-19	37	20	27.00
2	Red	Machine learning	36	20	29.00
3	Red	AI	36	21	21.00
4	Green	Deep learning	24	14	19.00

The potential of AI can revolutionize clinical practice [6], but to realize this potential several challenges must be addressed, including the lack of quality of medical data that can cause inaccuracy in the results obtained. By applying AI in clinical practice also has the potential to be limited in terms of data privacy, availability, and security; in addition, to achieve the desired results, it is very important to determining relevant clinical metrics and selecting an appropriate methodology. Then, in the conclusion of [6], it is stated that overcoming challenges like data quality, privacy, bias, and the need for human expertise is essential for responsible and effective AI integration.

Figure 8 shows the results of network visualization for several keywords related to the challenge. This result is obtained by selecting “Create a map based on text data”, with fields from which terms will be extracted in VOSviewer from the title and abstract fields. Then, the counting method chosen is “Full counting”. The keywords chosen are related to challenges and ensure that these keywords have a relationship with AI, healthcare, and challenges. In displaying this network visualization, the weight used is “Total link strength". The resulting visualization reveals a network structure in which the term "data" occupies the central position, with the largest node size, serving as the primary hub through which all other challenge-related keywords connect. Alongside "data", the term "artificial intelligence" appears as the second largest node positioned in the lower-center of the network, confirming that these two concepts together form the twin axes around which health AI challenge research revolves. The network is organized into three color-coded clusters that are interconnected through the central "data" node. The red cluster, occupying the upper portion of the network, groups "challenge" with "quality" and "availability". These three terms are tightly linked to one another and are all connected directly to the central "data" node, indicating that data quality and data availability are consistently framed as core dimensions of the broader implementation challenges discussed in the literature. The green cluster, occupying the lower and right portions, contains "artificial intelligence", "healthcare", and "bias"—the latter positioned at the far-right periphery with a visibly small node size. The placement of "bias" within the same cluster as "artificial intelligence" and "healthcare" yet at its extreme edge suggests that while algorithmic bias is recognized as relevant to AI-driven healthcare, it has not yet developed into a densely connected, central research theme in its own right. The blue cluster, positioned on the left side of the network, contains "security" and "privacy" in proximity to each other. Both terms are connected to the central "data" node, and also exhibit cross-cluster connections—"privacy" linking to "artificial intelligence" and "security" linking to "challenge"—indicating that these ethical concerns are not entirely isolated but have begun to intersect with core research topics. However, their small node sizes and peripheral positioning visually convey a pattern of acknowledged importance yet limited integration: security and privacy are recognized as concerns relevant to data and AI challenges, but their low occurrence frequency indicates that they remain peripheral themes rather than deeply embedded research priorities. The overall configuration presents a clear visual hierarchy of research attention.

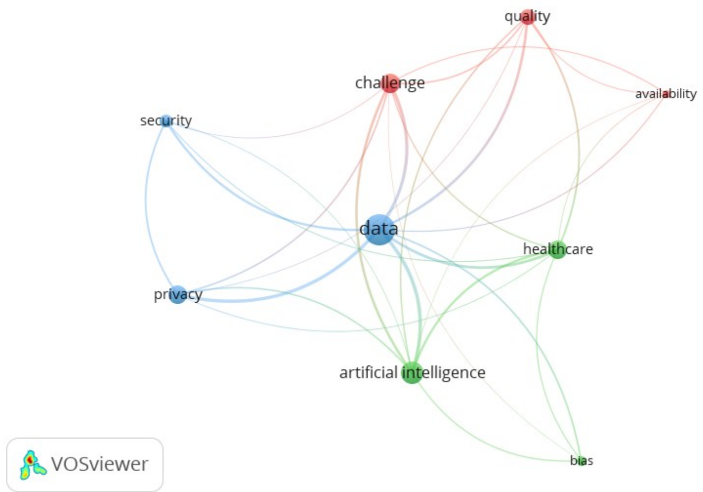

Figure 8. Keywords network visualization with the strength weight

3.2. Overlay visualization

Keyword occurrences in the published articles between 2019 and 2024 depicted in Figure 9. The color gradient, ranging from blue to yellow, represents the timeline of research focus from 2019 to 2024, with newer keywords highlighted in yellow and older ones in blue. The visualization demonstrates a clear thematic transition from pandemic-driven applications toward broader and more human-centered AI implementation in healthcare. Keywords such as "COVID-19", "coronavirus", and related clinical terms appear in blue-green tones, indicating that these topics dominated the earlier phase of the dataset and reflect the initial research emphasis on pandemic-related challenges, including disease prediction, rapid diagnosis, telemedicine, and healthcare management during the COVID-19 crisis.

Core methodological terms, including "machine learning", "artificial intelligence", and "deep learning", occupy central positions and are represented by green tones, suggesting sustained research attention during the intermediate period of the dataset. Their central location and extensive connections indicate that these methodologies evolved beyond pandemic-specific applications and became foundational technologies for broader healthcare use cases, including electronic health records, predictions models, diagnosis and medical imaging. The more recent topics represented by yellow tones, particularly “ChatGPT”, “knowledge”, “attitude”, “quality of life”, and related human-centered terms, are positioned toward the periphery of the network. Overall, the overlay visualization highlights the evolving research landscape from early pandemic-focused studies toward more mature AI methodologies and newly emerging interests in generative AI, education, and patient-centered healthcare innovation.

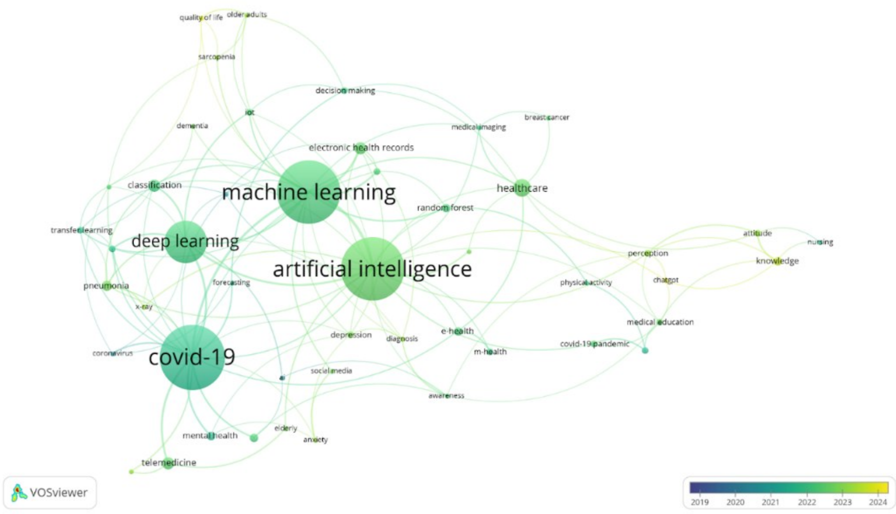

Figure 9. Keywords overlay visualization

3.3. Density visualization

The distribution and frequency of terms used in research related to health AI represented in Figure 10. The visualization uses color intensity to indicate keyword prominence, with bright yellow signifying high-density areas and darker shades of green and blue showing lower-density regions. “COVID-19”, “machine learning”, and “artificial intelligence” emerge as the central and most prominent terms, highlighted in the brightest yellow, indicating their significant presence and importance in the field.

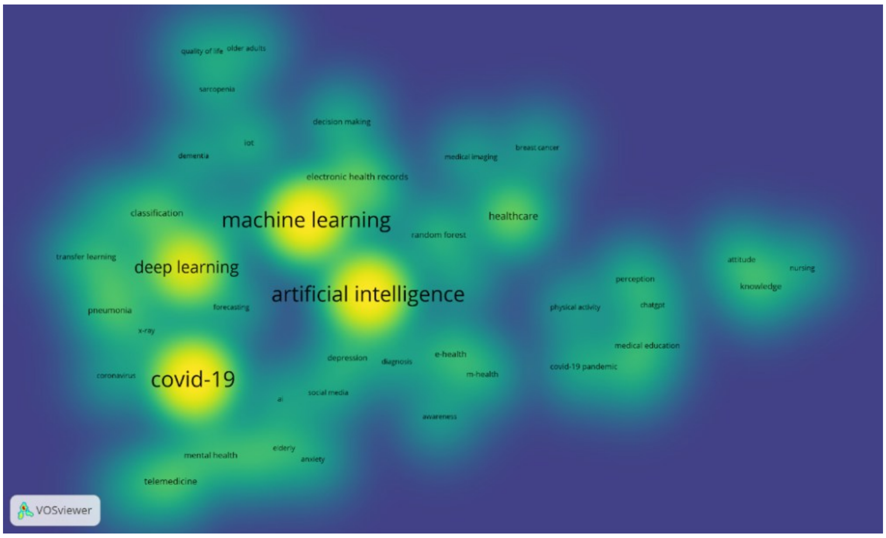

Figure 10. Keywords density visualization

The closely linked term “deep learning” also shows relatively high densities, signifying its frequent association with machine learning in this research domain. Peripheral keywords like “healthcare” are less dense, suggesting emerging areas within the broader scope. The spatial clustering and varied intensity of the terms provide insights into the dominant research trends and the interconnectedness of methodologies, challenges, and applications in AI-driven healthcare studies. This density map highlights both well-established topics and potential areas for future exploration.

Figure 11 shows the results of the density visualization of keywords related to the challenge, with the weight selected in displaying the visualization as “occurrences”. The visualization highlights “data” as the central and most intense keyword, indicating that data management is the fundamental bottleneck in Health AI implementation. Conversely, critical operational and ethical concerns like “privacy”, “security”, and “bias” appear in lower-density areas. This disparity suggests that while foundational data issues dominate the research landscape, specific regulatory and ethical barriers remain underexplored. Therefore, this highlights a clear research gap, emphasizing the need for future studies to develop standardized ethical frameworks for responsible AI integration.

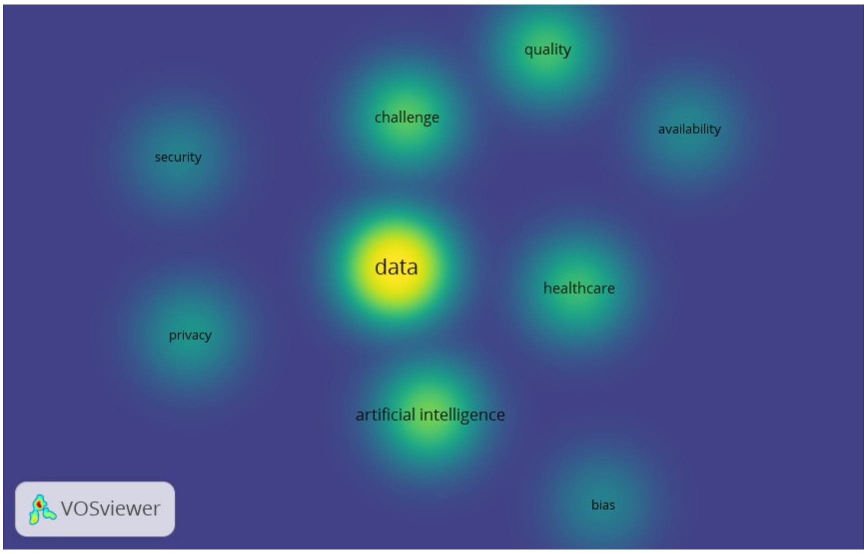

Figure 11. Keyword density visualization with the selected weight

3.4. Implications, limitations, and future research

Based on the findings, several actionable recommendations can be offered. For policymakers, the limited attention given to privacy, security, and bias underscores the urgency of establishing mandatory ethical auditing frameworks for healthcare AI systems, alongside standardized interoperability guidelines to reduce implementation fragmentation across healthcare institutions. For journal editors, the identified research gaps provide a basis for launching special issues or targeted calls for papers addressing neglected topics such as algorithmic fairness, data governance, privacy-preserving AI, and explainable healthcare systems. For researchers, two major weaknesses in current health AI research warrant particular attention. First, the separation between technical AI researchers and social-clinical researchers remains substantial, indicating the need for more interdisciplinary collaborations that integrate algorithm development with clinical, ethical, and human-centered perspectives. Second, the overlay analysis suggested that research attention often shifts rapidly from one trend to another (from COVID-19 to ChatGPT). The foundational challenges, such as bias mitigation, model transparency, fairness, and public trust, remain insufficiently addressed. Future studies should therefore prioritize longitudinal and implementation-focused research that evaluates the long-term safety, equity, and trustworthiness of AI systems in real-world healthcare settings.

This study is limited by the exclusive use of the MDPI database, which may introduce publisher bias and restrict coverage of studies indexed in broader databases such as Scopus and PubMed. Consequently, the findings may not fully represent the global Health AI research landscape. Future studies should expand database coverage by incorporating Scopus, Web of Science, and PubMed to improve dataset representativeness, validate thematic consistency, and enable more comprehensive bibliometric comparisons across publishers and disciplines. This study did not perform a stepwise screening and individual quality assessment, wherefore the article selection process did not follow the PRISMA protocol. All search results that met the initial filters were analyzed. Further research can adopt the full PRISMA workflow in quality assessment to ensure a more systematic and reproducible selection process.

4. CONCLUSION

Based on an analysis of MDPI articles, VOSviewer collectively highlights the dynamic and interconnected nature of research in health AI. Co-authorship networks reveal clusters of collaboration among researchers, with certain authors acting as key connectors, indicating interdisciplinary and global cooperation in the field. The keyword co-occurrence network illustrates the thematic structure of the domain, with "COVID-19", "machine learning", "artificial intelligence", and "deep learning" forming the core focus. The density visualization further emphasizes the dominance of "machine learning" and its related terms, underscoring their pivotal role in advancing healthcare AI applications. Simultaneously, less dense clusters like "healthcare", "medical education", and "classification", as well as keywords related to challenges, such as "privacy", "security", "bias", and "availability", suggest growing, yet still niche, subfields with opportunities for further exploration. Together, these visualizations provide an early comprehensive overview of the research landscape, highlighting the main players, dominant methodologies, and areas of potential growth in AI-driven healthcare innovation. In the end, VOSviewer has limited features. This tool does not have the feature to add the number of citations and h-index clusters, so it requires an additional tool.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the MDPI online journal system.

REFERENCES

[1] S. M. Varnosfaderani and M. Forouzanfar, "The role of AI in hospitals and clinics: transforming healthcare in the 21st century," *Bioengineering*, vol. 11, no. 4, Mar. 2024, doi: 10.3390/bioengineering11040337.

[2] S. A. Alowais *et al.*, "Revolutionizing healthcare: the role of artificial intelligence in clinical practice," *BMC Medical Education*, vol. 23, no. 1, 2023, doi: 10.1186/s12909-023-04698-z.

[3] C. D. Flynn and D. Chang, "Artificial intelligence in point-of-care biosensing: challenges and opportunities," *Diagnostics*, vol. 14, no. 11, 2024, doi: 10.3390/diagnostics14111100.

[4] X. Gao, P. He, Y. Zhou, and X. Qin, "Artificial intelligence applications in smart healthcare: a survey," *Future Internet*, vol. 16, no. 9, 2024, doi: 10.3390/fi16090308.

[5] A. Sarantopoulos *et al.*, "Artificial intelligence in infectious disease clinical practice: an overview of gaps, opportunities, and limitations," *Tropical Medicine and Infectious Disease*, vol. 9, no. 10, 2024, doi: 10.3390/tropicalmed9100228.

[6] S. Kalogiannidis, D. Kalfas, O. Papaevangelou, G. Giannarakis, and F. Chatzitheodoridis, "The role of artificial intelligence technology in predictive risk assessment for business continuity: a case study of Greece," *Risks*, vol. 12, no. 2, 2024, doi: 10.3390/risks12020019.

[7] S. K. Chettri, R. K. Deka, and M. J. Saikia, "Bridging the gap in the adoption of trustworthy AI in Indian healthcare: challenges and opportunities," *AI*, vol. 6, no. 1, 2025, doi: 10.3390/ai6010010.

[8] M. Hassan, A. Kushniruk, and E. Borycki, "Barriers to and facilitators of artificial intelligence adoption in health care: scoping review," *JMIR Human Factors*, vol. 11, 2024, doi: 10.2196/48633.
[9] M. Abdelwanis, M. C. E. Simsekler, A. F. Gabor, A. Sleptchenko, and M. Omar, "Artificial intelligence adoption challenges from healthcare providers' perspectives: a comprehensive review and future directions," *Safety Science*, vol. 193, 2026, doi: 10.1016/j.ssci.2025.107028.
[10] N. J. V. Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, 2010, doi: 10.1007/s11192-009-0146-3.
[11] L. Petersson *et al.*, "Challenges to implementing artificial intelligence in healthcare: a qualitative interview study with healthcare leaders in Sweden," *BMC Health Services Research*, vol. 22, no. 1, 2022, doi: 10.1186/s12913-022-08215-8.
[12] R. Farhat, A. R. A. Malik, A. H. Sheikh, and A. N. Fatima, "The role of AI in enhancing healthcare access and service quality in resource-limited settings," *International Journal of Artificial Intelligence*, vol. 11, no. 2, pp. 70–79, 2024, doi: 10.36079/lamintang.ijai-01102.709.
[13] N. Khalid, A. Qayyum, M. Bilal, A. Al-Fuqaha, and J. Qadir, "Privacy-preserving artificial intelligence in healthcare: techniques and applications," *Computers in Biology and Medicine*, vol. 158, 2023, doi: 10.1016/j.compbiomed.2023.106848.
[14] S. V. Chinta *et al.*, "AI-driven healthcare: fairness in AI healthcare: a survey," *PLOS Digital Health*, vol. 4, 2025, doi: 10.1371/journal.pdig.0000864.
[15] R. Challen, J. Denny, M. Pitt, L. Gompels, T. Edwards, and K. T. Atanasova, "Artificial intelligence, bias and clinical safety," *BMJ Quality and Safety*, vol. 28, no. 3, pp. 231–237, 2019, doi: 10.1136/bmjqs-2018-008370.
[16] P. Goktas and A. Grzybowski, "Shaping the future of healthcare: ethical clinical challenges and pathways to trustworthy AI," *Journal of Clinical Medicine*, vol. 14, no. 5, 2025, doi: 10.3390/jcm14051605.
[17] S. M. Williamson and V. Prybutok, "Balancing privacy and progress: a review of privacy challenges, systemic oversight, and patient perceptions in AI-driven healthcare," *Applied Sciences*, vol. 14, no. 2, 2024, doi: 10.3390/app14020675.
[18] M. M. Khan, N. Shah, N. Shaikh, A. Thabet, T. Alrabayah, and S. Belkhair, "Towards secure and trusted AI in healthcare: a systematic review of emerging innovations and ethical challenges," *International Journal of Medical Informatics*, vol. 195, Mar. 2025, doi: 10.1016/j.ijmedinf.2024.105780.
[19] Z. Sadeghi *et al.*, "A review of explainable artificial intelligence in healthcare," *Computers and Electrical Engineering*, vol. 118, 2024, doi: 10.1016/j.compeleceng.2024.109370.
[20] C. J. Kelly, A. Karthikesalingam, M. Suleyman, G. Corrado, and D. King, "Key challenges for delivering clinical impact with artificial intelligence," *BMC Medicine*, vol. 17, no. 1, 2019, doi: 10.1186/s12916-019-1426-2.
[21] R. Senthil, T. Anand, C. S. Somala, and K. M. Saravanan, "Bibliometric analysis of artificial intelligence in healthcare research: trends and future directions," *Future Healthcare Journal*, vol. 11, no. 3, 2024, doi: 10.1016/j.fhj.2024.100182.
[22] Y. Guo, Z. Hao, S. Zhao, J. Gong, and F. Yang, "Artificial intelligence in health care: bibliometric analysis," *Journal of Medical Internet Research*, vol. 22, no. 7, 2020, doi: 10.2196/18228.
[23] P. Pujari, G. Behl, A. H. Rizvi, K. Kakde, S. Suryawanshi, and S. Dingankar, "Bibliometric mapping of artificial intelligence applications in healthcare: a ScienceDirect and Scopus-based analysis," *Asia Pacific Journal of Health Management*, 2025, doi: 10.24083/apjhm.v20i2.4827.
[24] MDPI, "MDPI open access information and policy," mdpi.com. Accessed: May 14, 2026. [Online]. Available: https://www.mdpi.com/openaccess
[25] MDPI, "About MDPI journals," mdpi.com. Accessed: May 14, 2026. [Online]. Available: https://www.mdpi.com/about/journals
[26] MDPI, "MDPI instructions for authors," mdpi.com. Accessed: May 14, 2026. [Online]. Available: https://www.mdpi.com/authors
[27] M. S. Farooq, S. Riaz, A. Abid, T. Umer, and Y. B. Zikria, "Role of IoT technology in agriculture: a systematic literature review," *Electronics*, vol. 9, no. 2, 2020, doi: 10.3390/electronics9020319.
[28] B. Kitchenham and S. Charters, "Guidelines for performing systematic literature reviews in software engineering," *EBSE Technical Report*, Keele University and University of Durham, 2007.
[29] MDPI, *Increasing the visibility of scientific research since 1996*. Basel, Switzerland: MDPI, 2025. [Online]. Available: https://mdpi-res.com/data/mdpi-v20250604.pdf
[30] D. McPhee, "Molecules after 20 years—looking back and looking forward," *Molecules*, vol. 20, no. 1, pp. 645–647, 2015, doi: 10.3390/molecules20010645.
[31] Gannett-Tripp Library, "LibGuides: how to do research: a step-by-step guide: get started," libguides.elmira.edu. Accessed: Jun. 24, 2026. [Online]. Available: https://libguides.elmira.edu/c.php?g=184944&p=1221045
[32] L. Z. Atkinson and A. Cipriani, "How to carry out a literature search for a systematic review: a practical guide," *BJPsych Advances*, vol. 24, no. 2, pp. 74–82, 2018, doi: 10.1192/bja.2017.3.
[33] S. Wang *et al.*, "Technology to support aging in place: older adults' perspectives," *Healthcare*, vol. 7, no. 2, 2019, doi: 10.3390/healthcare7020060.
[34] M. S. A. Reshan *et al.*, "Detection of pneumonia from chest X-ray images utilizing MobileNet model," *Healthcare*, vol. 11, no. 11, 2023, doi: 10.3390/healthcare11111561.
[35] G. Battineni, N. Chintalapudi, and F. Amenta, "AI chatbot design during an epidemic like the novel coronavirus," *Healthcare*, vol. 8, no. 2, 2020, doi: 10.3390/healthcare8020154.
[36] N. N. Khanna *et al.*, "Economics of artificial intelligence in healthcare: diagnosis vs. treatment," *Healthcare*, vol. 10, no. 12, 2022, doi: 10.3390/healthcare10122493.
[37] M. H. Temsah *et al.*, "ChatGPT and the future of digital health: a study on healthcare workers' perceptions and expectations," *Healthcare*, vol. 11, no. 13, 2023, doi: 10.3390/healthcare11131812.
[38] M. M. Ahsan, R. Nazim, Z. Siddique, and P. Huebner, "Detection of COVID-19 patients from CT scan and chest x-ray data using modified mobilenetv2 and lime," *Healthcare*, vol. 9, no. 9, 2021, doi: 10.3390/healthcare9091099.
[39] Y. E. Almalki *et al.*, "A novel method for COVID-19 diagnosis using artificial intelligence in chest x-ray images," *Healthcare*, vol. 9, no. 5, 2021, doi: 10.3390/healthcare9050522.
[40] M. A. Amou, K. Xia, S. Kamhi, and M. Mouhafid, "A novel MRI diagnosis method for brain tumor classification based on CNN and Bayesian optimization," *Healthcare*, vol. 10, no. 3, 2022, doi: 10.3390/healthcare10030494.
[41] S. T. Tran, C. H. Cheng, T. T. Nguyen, M. H. Le, and D. G. Liu, "Tmd-unet: triple-unet with multi-scale input features and dense skip connection for medical image segmentation," *Healthcare*, vol. 9, no. 1, 2021, doi: 10.3390/healthcare9010054.
[42] G. Alwakid, W. Gouda, M. Humayun, and N. U. Sama, "Melanoma detection using deep learning-based classifications," *Healthcare*, vol. 10, no. 12, 2022, doi: 10.3390/healthcare10122481.

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