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ORIGINAL RESEARCH

Cyber-Organic Transformation: A Critical Approach to Artificial Intelligence Applications in Healthcare

Transformación ciberorgánica: un enfoque crítico de las aplicaciones de inteligencia artificial en los servicios de salud

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Resumen

Este estudio examina el papel creciente de la inteligencia artificial (IA), el aprendizaje automático (ML, machine learning) y las técnicas de aprendizaje profundo (DL, deeplearning) en la atención a la salud, a través de un análisis bibliométrico integral y una revisión de contenidos en la red basada en VOSviewer. Una evaluación de 4,637 artículos publicados entre 1992 y 2025 muestra que Estados Unidos, India, Reino Unido y China destacan tanto en volumen de publicaciones como en tasas de colaboración internacional. A nivel institucional, centros académicos líderes como la Universidad de Harvard (y sus Asociados Médicos) y la Universidad de Londres han desempeñado un papel pionero en el avance del campo. El análisis en redes por palabras clave destaca la creciente importancia de términos como inteligencia artificial, aprendizaje automático y aprendizaje profundo, junto con temas emergentes como sistemas de apoyo en la toma de decisiones clínicas, COVID-19 y grandes modelos de lenguaje (por ejemplo, ChatGPT), reflejando la creciente diversidad de la literatura. Los hallazgos bibliométricos destacan que las aplicaciones de IA para la atención a la salud cubren una amplia gama de dominios, incluida el procesamiento de imágenes clínicas, la supervisión remota de pacientes, la medicina personalizada y el procesamiento del lenguaje natural (NLP). El uso creciente de modelos de aprendizaje profundo en sistemas de apoyo para la toma de decisiones clínicas ilustra la creciente demanda de soluciones de salud digital en la era posterior a la COVID-19. Temas clave como la IA explicable (XAI), la privacidad de datos, consideraciones éticas y regulaciones legales se subrayan como dimensiones críticas para garantizar un progreso sostenible en el campo. La literatura también señala la importancia de conjuntos de datos más grandes y multicéntricos, colaboraciones internacionales más fuertes y la promoción de la alfabetización en IA como pasos esenciales hacia los avances futuros.

Palabras clave: inteligencia artificial; aprendizajeautomático; aprendizaje profundo; atención sanitaria; análisisbibliométrico

Abstract

The study examines the growing role of artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques in healthcare through a comprehensive bibliometric analysis and a VOSviewer-based network review. An evaluation of 4,637 articles published between 1992 and 2025 shows that the United States, India, the United Kingdom, and China stand out both in publication volume and in international collaboration (MCP) rates. At the institutional level, leading academic centers such as Harvard University (and its Medical Affiliates) and the University of London have played a pioneering role in advancing the field. Keyword network analysis highlights the rising prominence of terms including artificial intelligence, machine learning, and deep learning, along with emerging topics such as clinical decision support systems, COVID-19, and large language models (e.g., ChatGPT), reflecting the increasing diversity of the literature. Bibliometric findings emphasize that AI applications in healthcare cover a wide range of domains, including medical imaging, remote patient monitoring, personalized medicine, and natural language processing (NLP). The expanding use of deep learning models in clinical decision support systems illustrates the heightened demand for digital health solutions in the post-COVID-19 era. Key issues such as explainable AI (XAI), data privacy, ethical considerations, and legal regulations are underscored as critical dimensions for ensuring sustainable progress in the field. The literature also points to the importance of larger, multi-center datasets, stronger international collaborations, and the promotion of AI literacy as essential steps toward future advancements.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning; Healthcare; Bibliometric Analysis

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Introduction

The healthcare sector is undergoing a profound transformation driven by advances in artificial intelligence (AI), machine learning (ML), and deep learning (DL). The increasing volume of health data, combined with improvements in computational power and analytical methodologies, has facilitated the integration of AI-driven solutions into modern healthcare systems. [1] Since the late 1990s, the widespread adoption of digital health records, progress in medical imaging technologies, and the rise of big data analytics have provided fertile ground for the rapid expansion of AI applications in clinical practice. [2]

A bibliometric and VOSviewer-based analysis is employed to examine the extent to which AI-related concepts—such as artificial intelligence, machine learning, and deep learning—have been investigated in healthcare research. The analysis, conducted using the Web of Science (WoS) database, initially identified 4,662 articles published between 1992 and 2025. After removing 26 duplicate entries, a final dataset of 4,637 publications was systematically reviewed. The findings reveal a sharp acceleration in AI-related research within healthcare over the past decade, with an exponential increase in publication volume as the 2020s approached. [3]

An assessment of publication distribution indicates that leading institutions contributing to AI-driven healthcare research include Harvard University (and its Medical Affiliates), the University of London, and the University of California System. The most prominent journals publishing in this domain include *IEEE Access*, *Cureus Journal of Medical Science*, and *Diagnostics* (Guo et al., 2020). [4] On a national scale, the United States, India, the United Kingdom, and China emerge as dominant contributors, leading both in single-country publications (SCP) and in multi-country collaborations (MCP).[1]

VOS viewer-based network analyses and keyword density mapping highlight the emergence of distinct research clusters within AI applications in healthcare. Deep learning models have been predominantly applied to medical imaging and disease classification, forming a specialized research cluster. [5] Other research clusters revolve around clinical decision support systems, AI applications in COVID-19 diagnostics, telemedicine, and IoT-enabled healthcare solutions. [6] The recent surge of interest in large language models (LLMs, e.g., ChatGPT), natural language processing (NLP), and AI ethics further illustrates the diversification of AI research in healthcare. [7]

The rapid evolution of AI-related healthcare literature has led to tangible outcomes in areas such as healthcare service optimization, early disease detection, precision medicine, clinical decision support systems (CDSS), and remote patient monitoring.[4] However, as AI applications become more deeply embedded in clinical practice, several critical challenges have emerged, including data security, patient privacy, algorithmic bias, and ethical considerations.[3]

Beyond the technological dimension, the expansion of AI in healthcare raises pressing questions about equity, accessibility, and the broader social determinants of health. Research increasingly highlights that algorithmic bias, data gaps, and unequal access to digital infrastructure can reinforce or even exacerbate existing health inequalities. These concerns are particularly evident in low- and middle-income countries of the Global South, where limited resources and reliance on externally developed technologies create structural vulnerabilities. In this sense, mapping global publication and collaboration trends is not only valuable for tracking scientific progress but also crucial for understanding the power asymmetries and governance challenges that shape the transformative impact of AI in health systems.

This study provides a comprehensive examination of the trends, research gaps, and future challenges in AI-driven healthcare based on bibliometric findings and VOSviewer analyses. Additionally, it offers insights and recommendations for advancing AI applications in clinical practice, research, and health policy development.

Literature Review

Artificial intelligence (AI) in healthcare has evolved through distinct phases since the mid-20th century, with early applications in the 1970s primarily relying on expert systems. Broader adoption and major advancements were observed from the 2000s onward, driven by the availability of big data analytics and the proliferation of electronic health records (EHRs).[2] Since 2010, rapid improvements in machine learning (ML) and deep learning (DL), supported by enhanced computational capacity, have generated groundbreaking innovations in clinical practice.[1]

Early AI applications were largely rule-based, relying on predefined if-then algorithms that guided diagnostic processes. These systems, however, proved limited in detecting complex patterns within clinical.[3] By contrast, ML algorithms demonstrated superior pattern recognition capabilities by processing large volumes of heterogeneous medical data, enabling more generalizable and scalable healthcare solutions.[8]

A pivotal milestone in AI adoption came with the deployment of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in medical imaging. Deep learning models applied in radiology and pathology achieved high accuracy in lesion detection and tumor classification, substantially improving early disease diagnosis.[5] During the COVID-19 pandemic, automated diagnostic AI models proved essential in interpreting CT scans and X-ray images for rapid diagnosis and progression tracking.[9]

Beyond imaging, AI and ML algorithms have become the backbone of clinical decision support systems (CDSS), where EHRs are used to generate diagnostic recommendations, treatment plans, and risk stratifications. Gabriel et al. (2025)[3] emphasized that AI-based decision-support tools have enhanced patient care quality, particularly in cardiology, oncology, and neurology. Applications extend to hospital management, length-of-stay prediction, and emergency triage optimization, improving both resource allocation and clinical workflows.[12]
The pandemic also accelerated telemedicine and remote healthcare services, leading to smart health systems for quarantine protocols, remote monitoring, and decision support.[1] Deep learning models contributed to automated COVID-19 diagnosis, while AI-powered chatbots supported patient-provider communication by offering automated responses and symptom assessments.[9, 7]

Another active line of research focuses on natural language processing (NLP) and large language models (LLMs), including BERT, GPT-4, and ChatGPT, which are increasingly applied in medical text processing, disease symptom analysis, literature review automation, and doctor-patient interactions.[6] While these tools hold great promise, persistent concerns remain regarding algorithmic bias, data privacy risks, and accountability in AI-assisted medical decision-making.[7, 10]

Growing attention has also been given to explainable AI (XAI), which enhances physician trust in algorithmic systems by providing interpretable insights into predictions. These approaches aim to minimize diagnostic errors, strengthen patient safety, and reinforce the role of AI as a support system rather than a replacement for medical expertise.[3, 11] In parallel, precision medicine has emerged as a major field, where AI and ML integrate genetic, clinical, and behavioral datasets to enable personalized diagnostics and therapies. AI-powered precision medicine has advanced pharmacogenomics, drug discovery, and targeted cancer treatments, underscoring the shift toward individualized healthcare.[1, 6]

IoT-enabled wearable devices and home monitoring systems further contribute to real-time data acquisition, improving AI-driven health analytics for early intervention and preventive care. Such applications have proven valuable in chronic disease management, elderly care, and early warning systems.[12, 2]

Despite these advancements, AI models still require extensive, diverse, and representative datasets to achieve robust performance. Privacy restrictions, sensitive data regulations, and limited access to health records present significant obstacles.[3] Potential solutions include secure data-sharing frameworks, anonymized repositories, and synthetic data augmentation.[6] Nevertheless, most AI models continue to be evaluated in single-center studies with limited cohorts, raising concerns about generalizability.[5] The literature consistently emphasizes the need for large-scale, multi-center, and longitudinal trials to validate AI systems across diverse populations.

At the same time, equity and inclusiveness have become central issues in AI in healthcare research. Most large-scale datasets originate from high-income countries, raising doubts about applicability to underrepresented groups, particularly in the Global South. Scholars warn that algorithmic bias, data asymmetries, and infrastructure gaps may reinforce health inequalities when AI tools are deployed without contextual adaptation. Addressing these risks requires globally diverse data sources, transparent validation protocols, and strategies to reduce the digital divide.[10, 3]

In sum, the literature underscores both the remarkable advances and the persistent challenges in AI-enabled healthcare. Progress in medical imaging, CDSS, telemedicine, NLP, precision medicine, and IoT has demonstrated the transformative potential of AI, but its ethical, social, and equity implications demand continuous attention. Sustained interdisciplinary collaboration and international partnerships remain essential for ensuring that AI contributes to safe, inclusive, and equitable healthcare systems worldwide (Wang, 2025). [12]

Data and Methods

Bibliometric networks were constructed with VOS viewer. Keyword co-occurrence analysis applied an association-strength normalization and full counting scheme. The minimum occurrence threshold was set to 5, and sensitivity tests between 3 and 8 showed consistent clustering patterns, confirming the robustness of the chosen threshold. Community detection followed a modularity-based Louvain procedure with resolution 1.0, yielding k = 7 topic clusters in the final map. Labels were auto-placed with default weighting; manual overrides were limited to overlap removal without altering cluster membership. Country and author collaboration networks used full counting; single-country (SCP) vs. multi-country publications (MCP) were computed from WoS address fields. All queries ran on Web of Science Core Collection (extraction date: 10.03.2025) with documented inclusion/exclusion filters, and disambiguation steps addressed homonyms. Tool choices and normalization reflect established guidance in bibliometric mapping. [13], [14]

Data Collection

The research data were retrieved from the **Web of Science (WoS)** database using the **"Advanced Search"** function. To identify publications relevant to AI, ML, and DL in healthcare, the following keyword combinations were used:

- **"artificial intelligence" AND healthcare AND tool**
- **"machine learning" AND healthcare AND tool**
- **"deep learning" AND healthcare AND tool**

A total of **4,662** publications were retrieved through this query. The search focused on articles where the selected keywords appeared in the **title, abstract, or keywords fields**, ensuring that the dataset included publications directly related to AI applications in healthcare rather than those with superficial or indirect mentions (Aung et al., 2021; Guo et al., 2020). [15] [16]

After removing **26 duplicate records**, the final dataset consisted of **4,637 publications**. To ensure data integrity, WoS's **"Remove Duplicates"** function was supplemented with manual checks for exact matches in **title and DOI**. [2, 17]

Data Preprocessing

Effective bibliometric analysis requires rigorous data preprocessing. The following steps were undertaken:

- **Title and Abstract Review:** Articles with minimal relevance to healthcare (e.g., AI applications in engineering with no significant healthcare focus) were systematically reviewed and excluded.
- **Keyword Standardization:** Commonly interchangeable terms such as "AI" and "artificial intelligence" were normalized to a root form, ensuring consistency. Similarly, abbreviations like "ML" for "machine learning" and "DL" for "deep learning" were standardized. [18] [19]
- **Country and Institution Standardization:** Inconsistencies in institution and country names (e.g., "U.S.A.," "United States," "USA" or "Harvard Univ.," "Harvard University") were corrected to maintain uniformity.
- **Citation Count Validation:** The "Times Cited" field was validated against the extraction date (January 1, 2025). Where discrepancies were found, counts were cross-verified with WoS's "Citation Network". [20]

Following these preprocessing steps, the dataset was finalized, containing key metadata such as author names, institutions, countries, journal names, publication years, citation counts, and keywords.

Bibliometric Analysis

Bibliometric analysis is a **quantitative approach** used to evaluate the volume, distribution, and impact of scientific research in a given field.[18] The following analytical steps were applied:

1. **Author, Journal, and Institution Analysis:**

- Identification of the most prolific authors and institutions.

- Determination of the leading journals publishing AI-related healthcare research.
- Analysis of the most highly cited papers. [21]

2. **Publication and CitationTrends:**

- Assessment of the annual growth of publications and changes in average citation rates.
- Trend analysis to determine when AI research in healthcare experienced notable surges.[4]

3. **Country Performance Analysis:**

- **Single-Country Publications (SCP)** and **Multiple-Country Publications (MCP)** metrics were evaluated to measure the level of international collaboration.
- The global distribution of AI research in healthcare was examined to identify leading countries in the field.[4]

The raw bibliometric data were then imported into **VOS viewer**[13] to visualize research collaboration networks and keyword co-occurrence patterns. The following network analyses were performed:

- **Author Collaboration Network:**
- Identified **clusters of co-authorship**, highlighting key researchers and their contributions to specific subdomains (e.g., Tang, Allen Bibb, Celi).
- **KeywordCo-occurrence Network:**
- Examined **the frequency of co-occurring keywords** such as **"artificial intelligence," "machine learning," "deep learning," "telemedicine," "COVID-19," "ChatGPT,"** revealing the main thematic areas of AI research in healthcare. [22]
- **Country Collaboration Network:**
- Mapped international collaboration patterns, identifying which countries had the strongest research ties. [23]

By visualizing **research networks, key authors, thematic clusters,** and **country collaborations**, the **VOSviewer** analysis provided deeper insights into **the structure and trends in AI research in healthcare**.

Computational and Statistical Methods

The bibliometric data were analyzed using **Python and R programming languages**.

- **Python:**
- **Data manipulation and descriptive statistics** were conducted using **Pandas** and **NumPy**.
- **GeoPandas** was used to visualize the **geographic distribution of AI research in healthcare**.
- **R:**
- Bibliometric indicators and **network analyses** were performed using the **bibliometrix** and **biblioshiny** packages. [24]

The results were systematically structured into **tables and graphical representations** to facilitate interpretation.

Research Workflow Overview

The overall methodological approach followed these sequential steps:

1. **Data Collection** (Web of Science)
2. **Data Cleaning and Preprocessing**
3. **Descriptive Statistical Analysis**
4. **Network Analysis (VOS viewer)**
5. **Data Visualization**
6. **Interpretation of Results**

By integrating **quantitative** and **descriptive** methodologies, this study provides a **multi-dimensional perspective** on the research landscape of **AI and ML in healthcare**, uncovering key trends and research gaps in the field.

Findings and Evaluation

This section presents detailed findings from the bibliometric analysis and VOS viewer results based on the dataset. The analysis includes a comprehensive evaluation of authors, countries, journals, keywords, citation counts, and institutions. To enhance visualization, various maps, graphs, tables, and diagrams have been incorporated.

In the bibliometric analysis, the publication and citation performance of authors was initially examined, revealing a strong presence of multi-disciplinary collaborations across the dataset. When analyzing the top 25 most prolific authors (Figure 1), researchers such as *Li, J.* and *Kumar, S.* ranked at the top, each with more than 15 publications. This finding underscores the high research activity in areas such as clinical AI, medical imaging, and machine learning applications. [25]

In this analysis, the number of publications per author was visualized using a bar chart. The results indicate that the majority of these authors are affiliated with specialized research laboratories or clinical departments focusing on medical artificial intelligence. Given that multiple researchers share common names in the literature (e.g., several individuals named *Li, J.*), an identity verification process was conducted during data cleaning to ensure accurate citation matching.

Examining the distribution of publications from 1992 to 2025 (Figure 2), a notable increase in research activity was observed, particularly after 2010. While an anomalous peak in 1992 (>1,600 records) likely reflects indexing inconsistencies, the genuine peak occurred in 2024, with nearly 1,000 publications. Sensitivity analyses excluding the anomalous 1992 peak confirmed the robustness of this trend: steady growth until 2010, followed by exponential expansion throughout the 2020s. A similar upward trend was also noted in the average number of citations per publication.

Figure 1. Most prolific authors in AI and healthcare research (1992–2025)

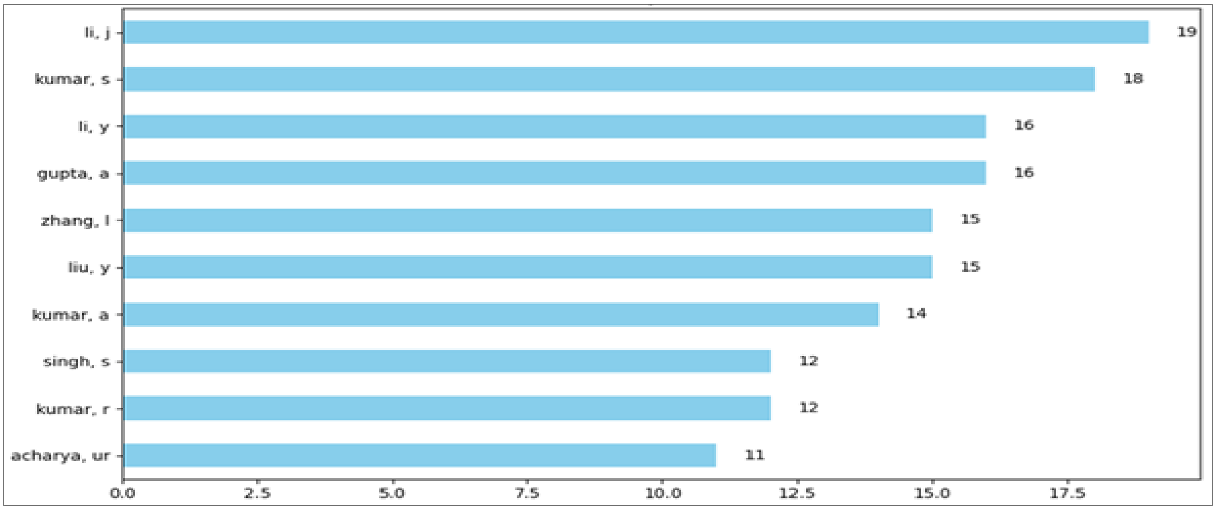
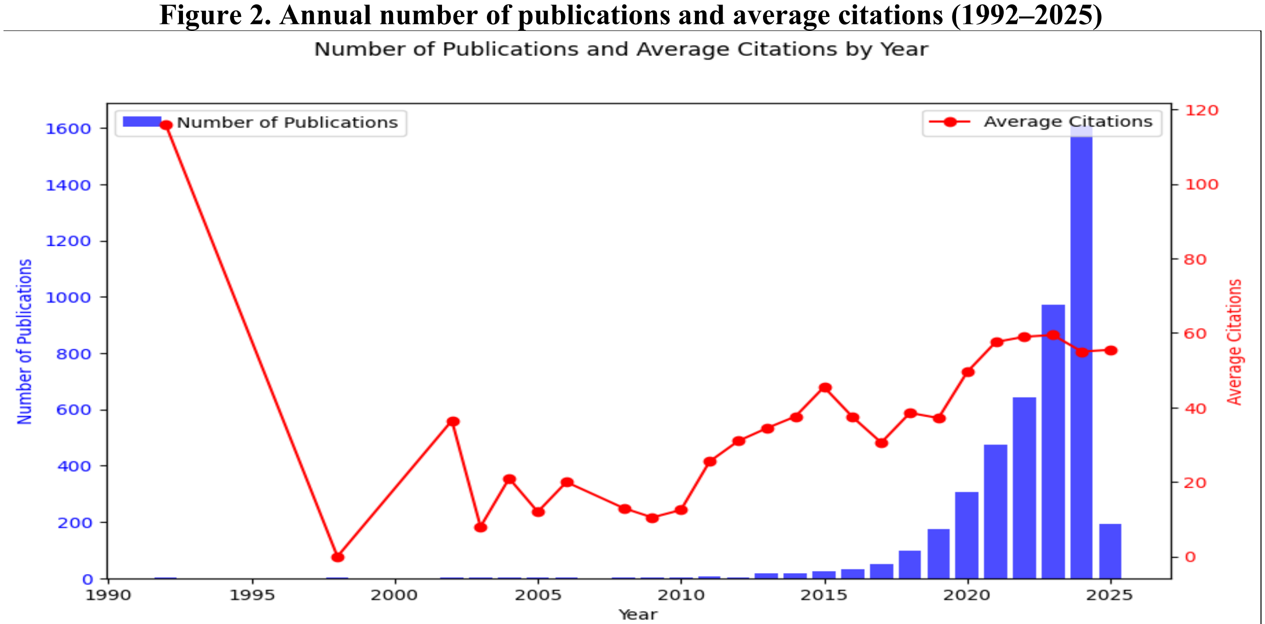


Figure 2. Annual number of publications and average citations (1992–2025)



In this visualization, the blue bars represent annual publication counts, while the red line illustrates the average citation trend for the corresponding years. The surge in research output since 2020 can be attributed to several factors:

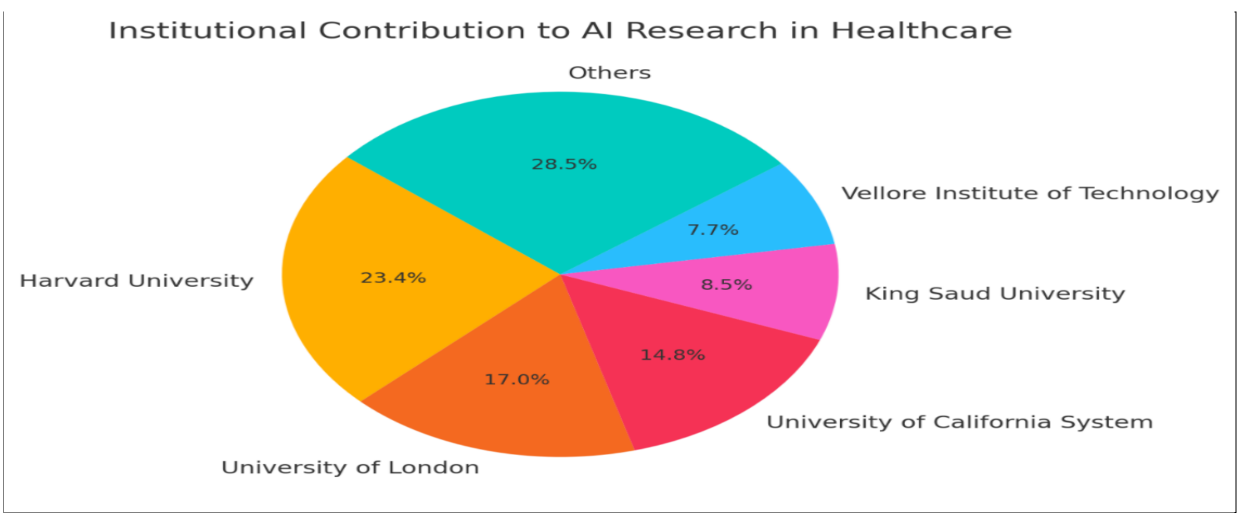
- The maturation of big data technologies,
- Increasedcomputationalpower,
- Growing demand for digital health solutions in the aftermath of the COVID-19 pandemic,
- The widespread acceptance of clinical decision support systems, despite ongoing ethical and regulatory considerations.

These patterns align with previous bibliometric studies on AI in healthcare.[4, 15]
Another key aspect of bibliometric analysis is assessing the research performance of institutions. The dataset reveals that Harvard University, the University of London, and the University of California System are among the leading contributors in this field. The dominance of institutions from the United States and the United Kingdom may be attributed to robust funding opportunities and the extensive academic networks present in these countries.

Institutional outputs were next profiled to understand organizational leadership in AI-health publications (Figure 3). The distribution shows substantial contributions from Harvard University (including its medical affiliates), the University of London, and the University of California System. The presence of King Saud University and Vellore Institute of Technology underscores widening geographic participation beyond traditional hubs. Interpretation should consider the aggregation choices documented in preprocessing (institution name standardization) and the selection criterion used for the chart (Top-5 institutions; remainder grouped as "Others").

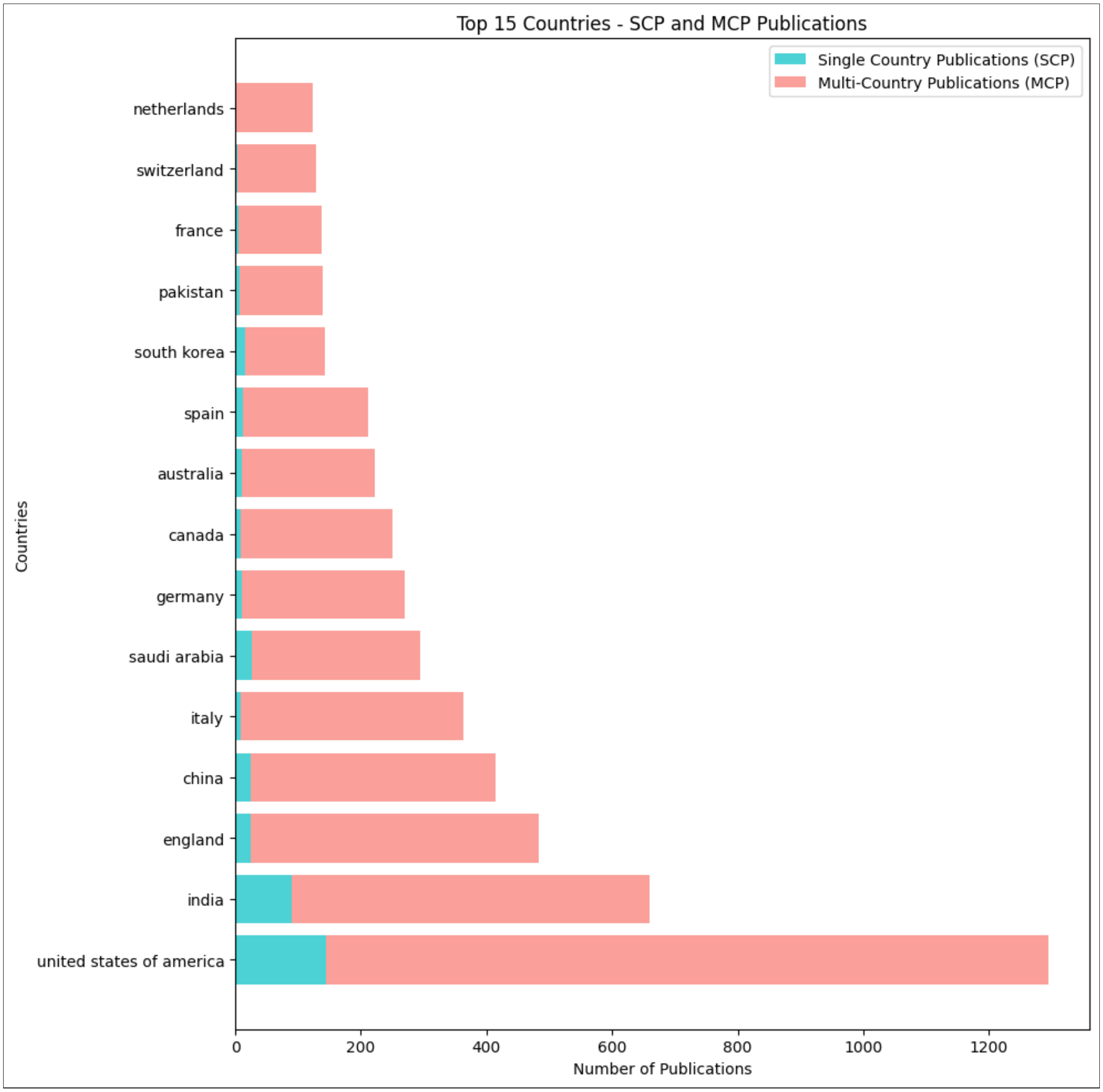
Country-level activity and collaboration intensity were analyzed using Single-Country Publications (SCP) and Multi-Country Publications (MCP) (Figure 4). The United States leads overall output and acts as a major collaboration hub, while India, the United Kingdom, China, and Italy also display strong activity. Interpreting SCP alongside MCP highlights structural patterns: high output with lower MCP% suggests domestically concentrated leadership, whereas modest output with higher MCP% indicates collaboration-dependent visibility. For clarity, the figure reports absolute SCP and MCP counts and annotates MCP% = MCP / Total for each country.

Figure 3. Institutional Contribution to AI Research in Healthcare



Source: Authors' analysis based on WoS (extraction: 10 Mar 2025).
Note: Shares reflect the proportion of articles per institution among the Top-5; the **Others** section pools remaining institutions.

Figure 4. SCP and MCP Values of Countries (Top-15 by output)

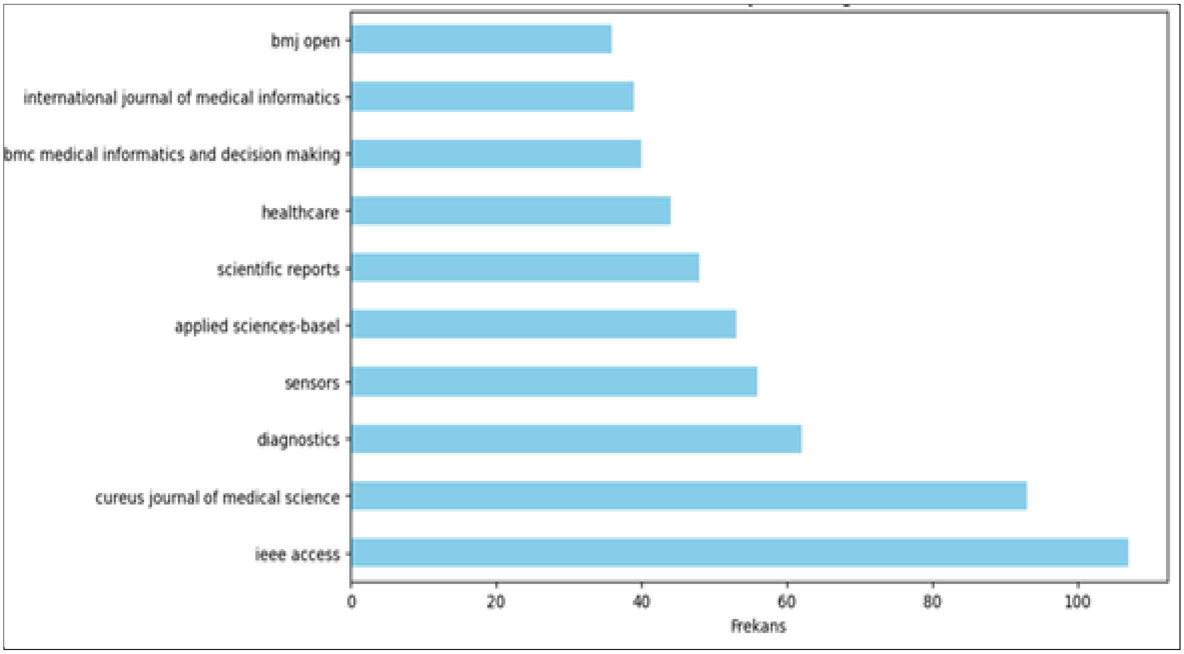


Source: Authors' analysis based on WoS (extraction: 10 Mar 2025).
Note: **Teal = SCP; Salmon = MCP.** Labels show **MCP%**. Full counting from address fields; selection = Top-15 countries by total publications.

Journal venues were examined to understand where AI-health research is published (Figure 5). The ranking by article count shows *IEEE Access* at the top, followed by *Cureus* and *Diagnostics*. Outlets such as *Sensors* and *Applied Sciences-Basel* reflect the field's interdisciplinary character, while *Scientific Reports*, *Healthcare*, and *BMC*

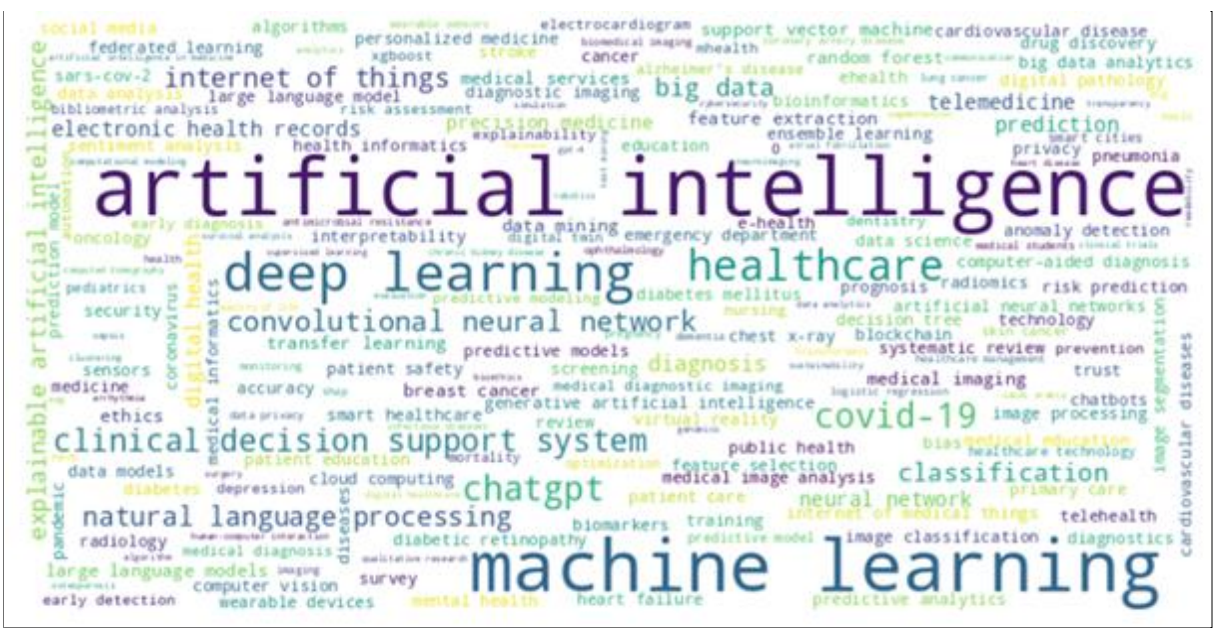
Medical Informatics and Decision Making indicate the growing footprint within medical informatics. Counts represent number of articles in the dataset, not citation totals; therefore wording in the text and caption emphasizes publication frequency rather than "most cited."

Figure 5. Top 10 Journals by Article Count



Source: Authors' analysis based on WoS (extraction: 10 Mar 2025).
Note: Bars show the number of dataset articles per journal (not citation counts).

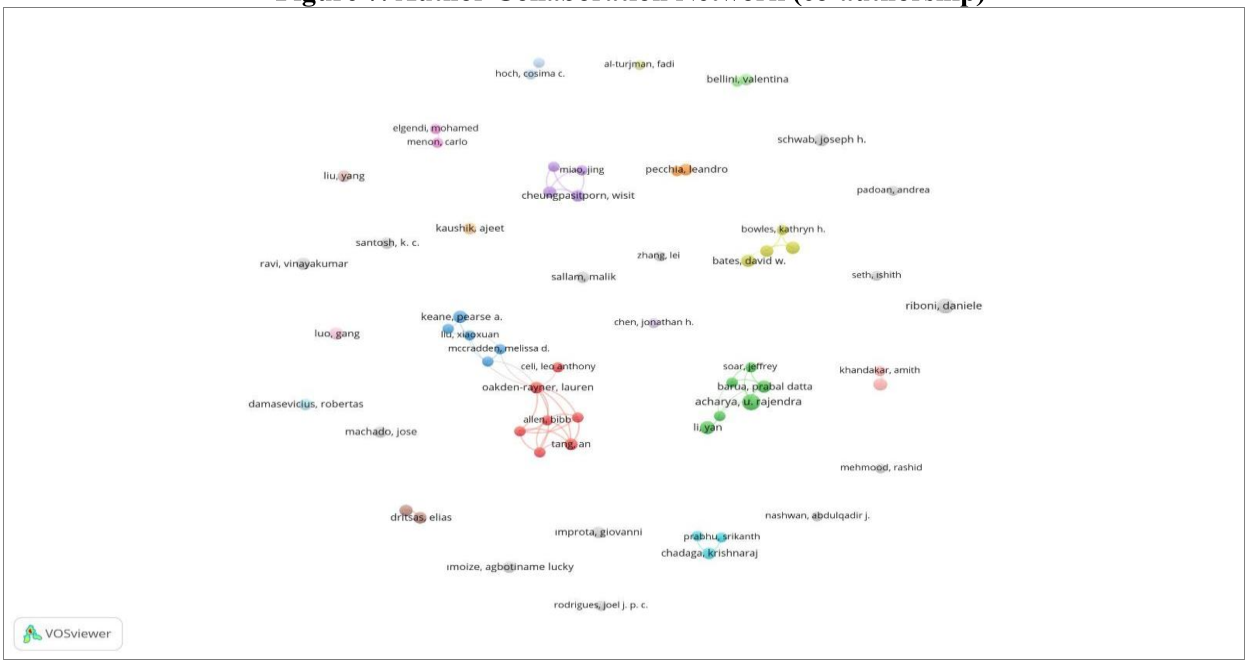
Figure 6. Keyword Distribution (Word Cloud)



Source: Authors' analysis based on WoS.
Note: Terms normalized as described in preprocessing; stop-words removed; font size ∝ frequency

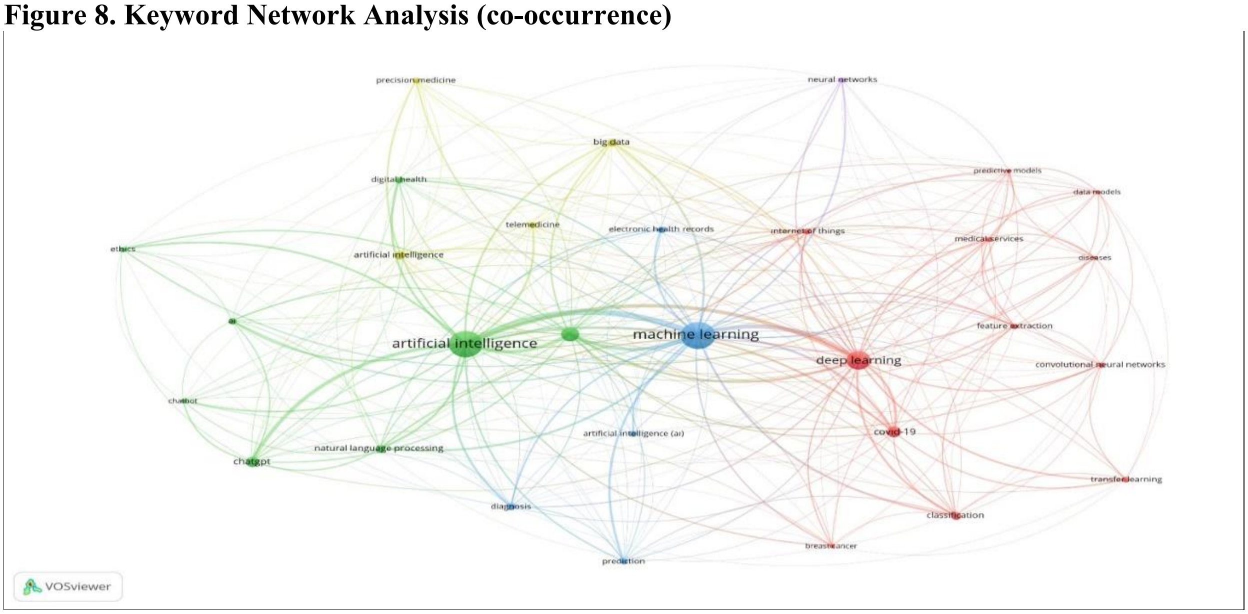
Keyword salience and emerging topics were summarized via a word-cloud (Figure 6) for an at-a-glance view. High-frequency terms include artificial intelligence, machine learning, deep learning, healthcare, clinical decision support system, Internet of Things, and COVID-19. The growing presence of large language models (e.g., ChatGPT) and "explainable AI (XAI)" signals attention to trustworthy and interpretable systems; however, interpretation relies on the more rigorous co-occurrence network in Figure 8.

Figure 7. Author Collaboration Network (co-authorship)



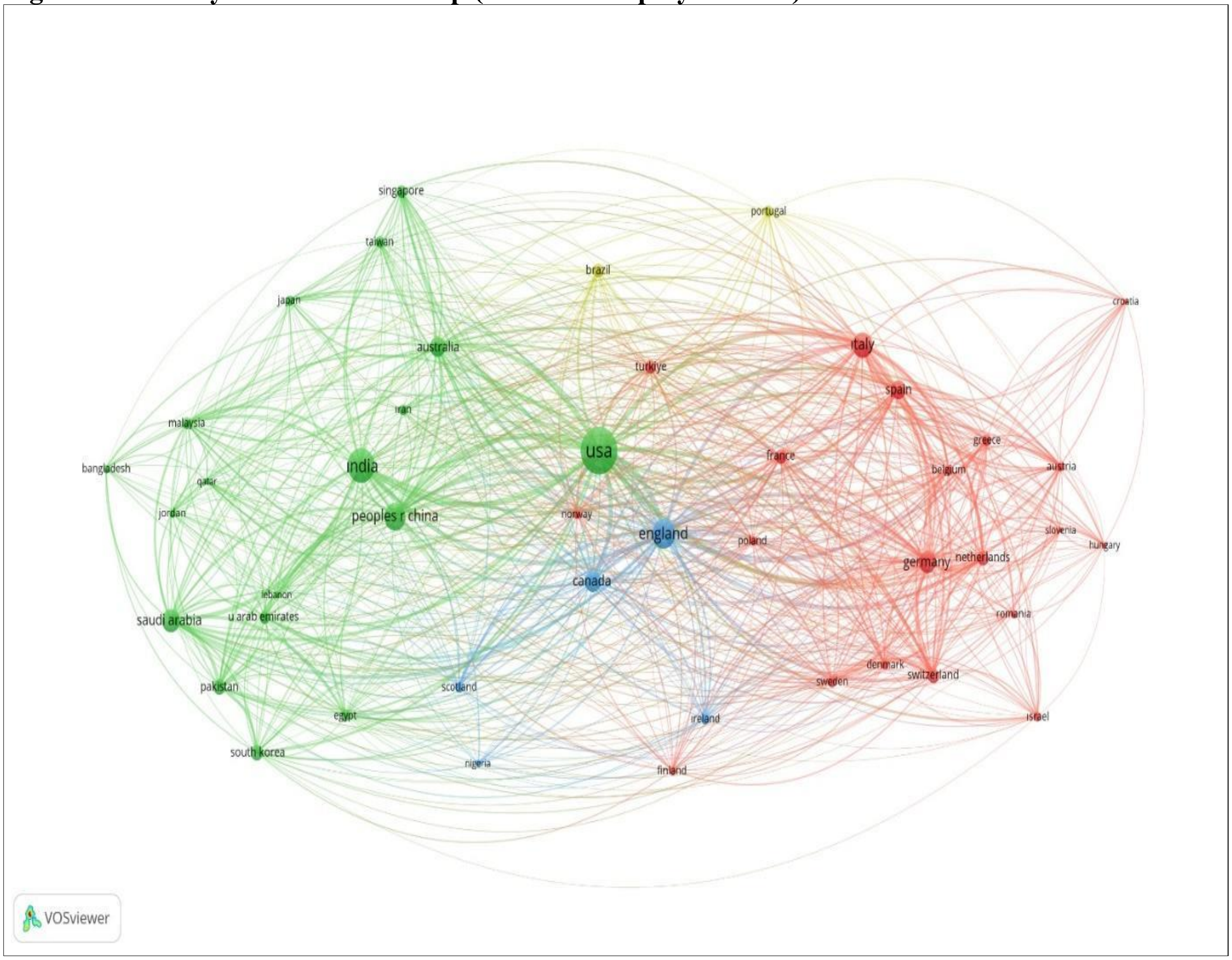
Source: VOSviewer; WoS data (extraction: 10 Mar 2025).
Note: Full counting; labels auto-placed; identity disambiguation followed the preprocessing protocol.

Figure 8. Keyword Network Analysis (co-occurrence)



Source: VOSviewer; WoS data (extraction: 10 Mar 2025).
Note: **Min keyword occurrences = 5; normalization = association strength; clustering = Louvain (resolution = 1.0); k = 7.**

Figure 9. Country Collaboration Map (co-authorship by address)



Source: VOSviewer; WoS data (extraction: 10 Mar 2025).
Note: Full counting; edges weighted by co-authored publications; colors denote Louvain clusters.

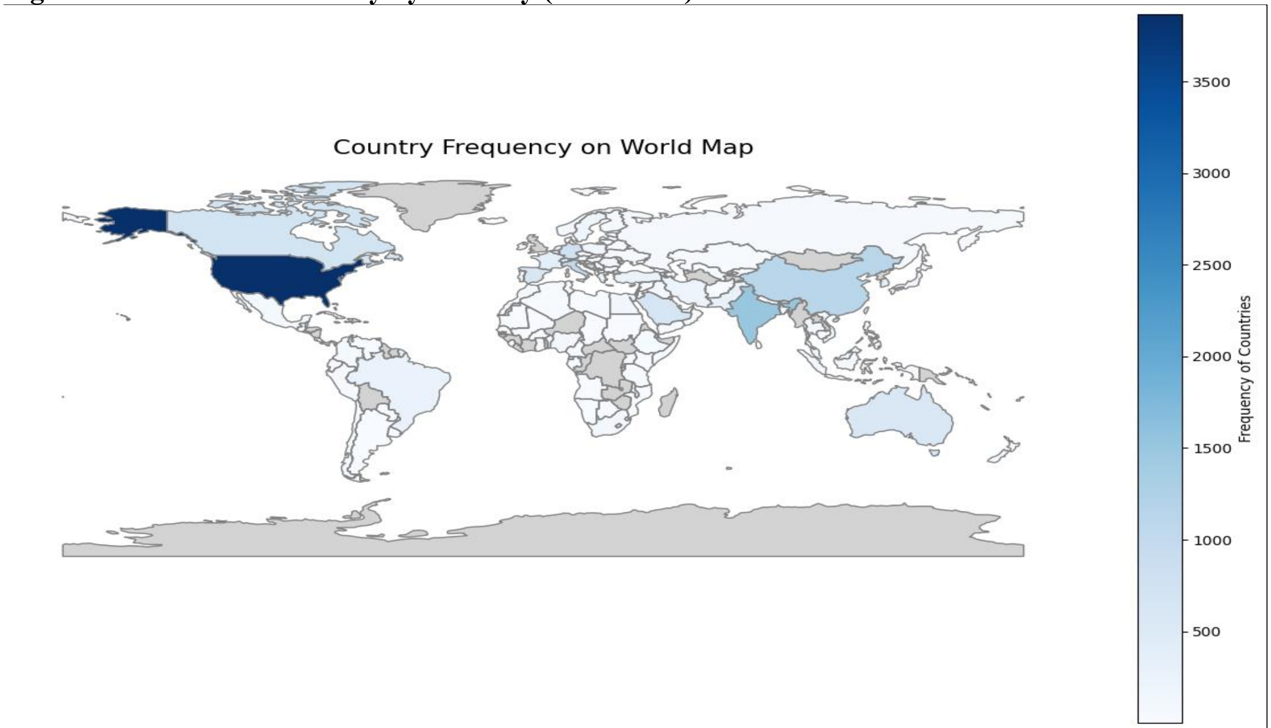
Author collaboration patterns reveal clustered co-authorship communities (Figure 7). Central figures include Tang, Allen Bibb, Celi, and Oakden-Rayner, reflecting active networks in clinical AI, radiology, and imaging. Node sizes indicate total link strength; colors denote clusters. Results should be read together with the inclusion thresholds documented in Methods to avoid misattribution for common surnames.

Keyword co-occurrence mapping identifies seven thematic clusters that structure the field (Figure 8). A core triad formed by artificial intelligence, machine learning, and deep learning connects to subdomains such as telemedicine, big data, and electronic health records. Newer topics—explainable AI, ethics, and large language models—appear in more recent clusters, indicating a shift toward trust, governance, and language-based tools.

The country collaboration network shows a dense component centered on the United States, with a prominent Asia-based cluster led by India and China and a highly interconnected European cluster (Figure 9). Link densities reflect repeated co-authorship across borders. Reading this network alongside Figure 4 clarifies how collaboration intensity (MCP%) varies with overall output.

A choropleth map summarizes publication density by country (Figure 10). Darker shades correspond to higher counts, with the United States, India, China, and the United Kingdom standing out. Because full counting is used, multi-country papers contribute to each participating country; absolute counts should therefore be interpreted with this caveat in mind.

Figure 10. Publication Density by Country (1992–2025)



Source: Geopandas visualization of WoS address fields (extraction: 10 Mar 2025).
Note: Full counting; legend shows article counts in the dataset.

The conducted analyses reveal that AI and machine learning applications in healthcare have gained remarkable momentum in recent years. Based on the bibliometric data, the following key insights can be drawn:

- U.S. Leadership and Global Collaborations

The United States leads in both single-country publications (SCP) and multi-country publications (MCP), confirming its dominance in research and funding capacity in this field. Meanwhile, India and China are emerging as rapidly growing contributors, supported by increasing international collaborations.

- Harvard University's Leading Role Among Institutions

Institutions such as Harvard University and the University of London have a high number of publications, largely driven by their medical schools and research centers focusing on health informatics.

- Integration of Machine Learning and Deep Learning

Both machine learning (ML) and deep learning (DL) methods are increasingly being adopted in medical imaging analysis and patient record processing. A recent example of this trend is the widespread use of deep learning models in COVID-19 diagnosis.

- Emerging Trend: ChatGPT and Ethical Considerations

The increasing presence of terms such as *ChatGPT* and *large language models* in the literature highlights the expanding role of AI-driven text analytics, patient-doctor interactions, and clinical decision support systems. Additionally, discussions on "explainable AI," "transparency," and "ethics" have gained prominence.

- Journal Preferences and Fast-Publishing Platforms

The popularity of open-access and rapid peer-review journals such as *IEEE Access* and *Cureus* reflects researchers' growing preference for faster dissemination of findings to a broader audience.

Overall, research on AI and machine learning in healthcare has gained significant momentum in both academic and industrial sectors. Future studies are expected to focus on data privacy, ethics, legal frameworks, and AI explainability. Furthermore, the growing participation of institutions from the Global South, although still comparatively limited, highlights the need to strengthen inclusivity and address structural inequalities in global AI-health research. The continued increase in international collaborations and the development of multi-disciplinary teams will further enhance the diversity, quality, and impact of publications in this field.

Conclusion

This study provides a comprehensive analysis of publications focusing on artificial intelligence (AI), machine learning (ML), and deep learning (DL) applications in healthcare through bibliometric analysis and VOSviewer network analysis. By evaluating 4,637 publications from the Web of Science database spanning 1992–2025, key findings have been identified.

Over the years, research in AI, ML, and DL in healthcare has shown an exponential increase, particularly after 2010, driven by advancements in health informatics and medical AI technologies. The peak publication year of 2024 highlights the growing interest in this domain.

Key Findings:

- **Institutions:** Leading institutions such as Harvard University (including its Medical Affiliates) and the University of London have played a dominant role in research output. This underscores the importance of multidisciplinary research ecosystems and strong financial support within these universities.
- **Countries:** The United States remains the global leader in AI healthcare research, while India, the United Kingdom, China, and Italy have also shown increasing contributions in both single-country publications (SCP) and multi-country publications (MCP). Asian countries, particularly India and China, have expanded their research output through government-supported initiatives in medicine and engineering.
- **Keyword Trends:** In addition to core terms such as "artificial intelligence," "machine learning," and "deep learning," rapidly emerging concepts like "COVID-19," "ChatGPT," "clinical decision support system," "Internet of Things (IoT)," and "big data" reflect the increasing digitalization of clinical processes and the expansion of remote healthcare services.
- **Journals:** *IEEE Access*, *Cureus*, and *Diagnostics* frequently publish research on health informatics and medical AI. Articles published in these journals tend to receive high citation rates and gain rapid visibility.
- **Author Collaboration Network:** Researchers central to the network are primarily focused on clinical AI and medical imaging, highlighting their significant contributions to these specialized fields.
- **Keyword Co-occurrence Network:** Strong connections between "artificial intelligence," "machine learning," and "deep learning" demonstrate their interdependent nature. Additionally, emerging concepts such as "ChatGPT" and "explainable AI" (XAI) are gaining prominence.
- **Country Collaboration Network:** The United States remains the central hub for global collaborations, while distinct Europe–Asia research clusters continue to expand. Countries such as India, China, the United Kingdom, and Italy are forming intensive research partnerships.

Future Directions:

- Enhancing data sharing and standardization will improve the generalizability of research findings.
- Adopting explainable AI (XAI) methods in clinical decision support systems will enhance trust among physicians and patients.
- Encouraging international projects will facilitate the development of interdisciplinary and multi-center datasets, enabling more effective AI applications.
- Integrating AI literacy programs into medical and engineering education will strengthen sectoral and academic adaptation.
-

Overall Evaluation : The volume and impact of AI research in healthcare are continuously growing, with interdisciplinary collaborations expanding globally. However, research remains unevenly distributed, with limited participation from institutions in the Global South, highlighting the need for more inclusive international collaborations. The study results indicate that this rapid growth will persist, with personalized medicine, remote healthcare services, explainable AI, and data security becoming even more critical in the future. Both academic research and industrial applications are expected to create new opportunities for patient care and public health. Therefore, the sustainable and multidimensional development of AI in healthcare will depend on the collective efforts of stakeholders, including academia, industry, regulatory bodies, and healthcare professionals.

Discussion and Recommendations

The bibliometric and VOS viewer analyses conducted in this study demonstrate a significant increase in the application of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in healthcare, particularly after 2010. This growth is primarily driven by the expanding volume of medical data, advancements in computational power, and the increasing demand for clinical decision support systems (CDSS). [1, 26, 27]

The findings confirm that the United States leads AI research in healthcare, with institutions such as Harvard University, the University of California System, and Stanford University playing pivotal roles. This leadership is supported by substantial academic and industrial collaborations, as well as diverse research funding opportunities that encourage interdisciplinary studies.[3, 48] Additionally, international collaborations have enabled the United States to maintain its dominance in high-impact AI research, further strengthening its global influence in healthcare AI development.[8 28]

Concerns about the governance and safety of AI systems in healthcare remain central to ongoing debates. As Macrae (2019) [29] emphasizes, the safe adoption of artificial intelligence requires not only technical validation but also the establishment of robust regulatory and institutional frameworks that ensure accountability, transparency, and resilience against potential risks.

Beyond the United States, countries such as India, the United Kingdom, China, and Italy have emerged as key contributors to AI-driven healthcare research. India, for instance, has demonstrated significant growth in machine learning and medical data analytics, largely attributed to its high population and state-backed AI research initiatives.[6, 30] Meanwhile, China has become a leader in big data analytics, medical imaging, and deep learning applications, with strong government-led AI initiatives fostering university–private sector collaborations to accelerate AI adoption.[4,16]

Journals such as *IEEE Access* and *Cureus* have been among the most preferred publication venues, primarily due to their open-access policies and rapid peer-review processes.[3] Additionally, *Diagnostics* and *Sensors* have expanded their publication volume on AI-driven healthcare applications, accelerating the real-world adoption of AI innovations in medical settings. [31]

Although this analysis did not explicitly measure ethical and legal concerns, the increasing frequency of terms such as “ethics” and “explainable artificial intelligence (XAI)” highlights the growing importance of AI transparency and fairness in healthcare.[8 32] Privacy concerns regarding patient data processing, the transparency of AI-driven decision-making, and bias-related issues are becoming key topics in contemporary AI research.[49, 33] Future studies are expected to place a stronger emphasis on these ethical considerations, making them an integral part of health informatics research and policy discussions. [34]

The quality and diversity of datasets play a critical role in determining the effectiveness of AI models. Standardizing medical datasets across countries and healthcare institutions would improve the generalizability and robustness of AI-driven solutions.[1, 35] Moreover, explainable AI (XAI) is crucial in enhancing clinicians’ trust in AI-based decision-support systems.[3,11] Techniques such as attention mechanisms, feature importance analysis, and interpretable modeling should be integrated into clinical workflows to improve transparency and accountability. [36, 37]

At present, many AI models are validated using limited patient cohorts, restricting their generalizability.[4] Long-term, multi-site clinical trials across diverse demographic groups are essential to evaluate AI's real-world effectiveness.[38] [39] Additionally, legal and ethical barriers to data sharing often hinder large-scale AI projects, restricting them to regional implementations. However, international AI research consortia—such as Horizon 2020 (H2020) in the European Union and joint U.S.–E.U. collaborations—could facilitate AI-driven healthcare innovations by enabling large-scale data-sharing frameworks.[6, 40]

Future Implications and Policy Recommendations

- **AI Literacy in Healthcare:** The integration of AI literacy programs into medical and healthcare professional training is essential for ensuring the effective and ethical use of AI technologies.[12, 41] Healthcare professionals, including doctors, nurses, and medical administrators, must develop a fundamental understanding of AI concepts to fully leverage its potential.[42]
- **Remote Patient Monitoring and Post-Pandemic Applications:** In the post-pandemic era, AI's role in telemedicine, remote patient monitoring, and disease diagnostics has expanded significantly. Tools like ChatGPT and other large language models are increasingly integrated into clinical report writing, doctor-patient interactions, and medical text processing.[1, 26, 43]
- **Temporal Trend Analysis and Health Outcomes:** Many recent studies emphasize robust trend analyses[44], [45] —for instance, employing linear, joinpoint, or nonlinear models—to detect changes in healthcare outcomes.[46] As healthcare systems evolve, integrating AI with time-series data can help capture shifts in disease incidence, health service use, and patient behavior.[32, 47]
- **Filling Research Gaps:** Some areas, such as fetal medicine,[28] integrated care,[30] or specialized domains like orthopedic biofilm research[48] and genomics,[38] have unique data needs and methodologies. Extending AI solutions into these focused specialties can advance precision medicine and further interdisciplinary collaboration.[37]

Limitations

This study has several limitations. The dataset was derived solely from the Web of Science (WoS) database, meaning that other databases such as Scopus, IEEE Xplore, PubMed, and Google Scholar were not included.[31] Additionally, the search terms used in this study ("artificial intelligence," "machine learning," "deep learning," and "healthcare and tool") may have excluded some relevant studies that employed different terminologies. The analysis was also limited to English-language, peer-reviewed journal articles, meaning that conference papers, non-English publications, and other gray literature were not included.[33, 49] Nevertheless, with a dataset covering 4,637 publications spanning nearly three decades, this study offers a comprehensive and data-driven overview of the emerging trends in AI-driven healthcare research. Future work could extend the dataset by integrating Scopus, IEEE Xplore, and PubMed databases to provide a more holistic and comprehensive perspective.

AI and machine learning in healthcare continue to expand at an unprecedented rate, with particular emphasis on big data analytics, medical imaging, decision support systems, remote patient monitoring, and clinical data management. The United States, the United Kingdom, India, and China remain leading contributors, while international collaborations are increasingly driving interdisciplinary AI research on a global scale.[34,32]

The future of AI in healthcare will be shaped by explainability, ethics, and data privacy concerns. Addressing these challenges is critical for building trust among healthcare professionals and patients, ensuring that AI becomes an indispensable tool for modern healthcare systems.[8, 31] Through collaborative efforts among academia, industry, and regulatory bodies, AI's potential will be further expanded, leading to groundbreaking developments in disease diagnosis, personalized medicine, and public health management.[1, 3, 6]

Critical Reflections

While this study maps the descriptive and quantitative growth of AI in healthcare, future research must go beyond bibliometric trends to critically assess the transformative impact of these technologies. Questions of how AI reshapes knowledge production, clinical authority, and the digital divide between the Global North and South remain central to understanding its broader implications. Moreover, quality-based metrics—such as average citations per paper, journal impact factors, and h-index—should be incorporated alongside volume-based indicators to capture the real influence of global collaborations. Finally, future scholarship should explicitly examine how AI affects healthcare accessibility, equity, and social justice, ensuring that technological progress aligns with public health goals and contributes to health activism.

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Author Contributions
The **entire study** was conducted **solely by the author**, including:

- **Conceptualization and studydesign**
- **Data collection and processing**
- **Bibliometric and networkanalysis**
- **Manuscriptwriting and revisions**

The author takes full responsibility for the content and integrity of this research.

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