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Mapping artificial intelligence applications in electronic medical records research

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ABSTRACT

The integration of electronic medical records (EMR) and artificial intelligence (AI) in healthcare improves data accessibility, security, diagnostic accuracy, personalized care, and overall system performance. Despite increasing interest, a comprehensive understanding of the field's development, key contributions, and dominant research themes remains limited. This study presents a bibliometric analysis of 681 articles selected from 1893 initial records retrieved from the Scopus database (2015–2025) using the keywords "electronic medical record" AND "artificial intelligence." Data were analyzed using Microsoft Excel for trend analysis and VOSviewer for keyword co-occurrence and thematic clustering. Results show steady publication growth, mainly from developed countries and health informatics institutions. Four main research themes emerged: i) AI adoption in healthcare systems, ii) patient characteristics and clinical assessment, iii) predictive models and machine learning (ML) algorithms, and iv) deep learning (DL) and diagnostic accuracy. Nevertheless, research gaps persist in areas such as patient safety, data privacy, ethical issues, primary care implementation, healthcare workforce roles, and specific algorithmic approaches. Trust in AI systems also requires deeper investigation.

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1. INTRODUCTION

The rapid advancement of information and communication technology (ICT) has significantly transformed healthcare systems worldwide, enabling improved access to health information and more efficient service delivery [1]. A critical component of this transformation is the electronic medical record (EMR), which digitally stores sensitive patient data such as medical history, laboratory results, medications, and diagnostic imaging [2]. EMRs enhance healthcare delivery through automated data collection, interoperability, and improved data security, helping to reduce errors and the risk of cyber threats [3], [4].

The COVID-19 pandemic further accelerated the adoption of digital technologies in healthcare, including EMRs, as governments and institutions prioritized digital infrastructure to ensure continuity of care [5]. In this digital shift, artificial intelligence (AI) has emerged as a transformative force with the potential to enhance clinical decision-making, personalize patient care, and improve operational efficiency [6], [7]. Specifically, AI enables the extraction and analysis of complex, unstructured EMR data, aiding in risk prediction, documentation accuracy, and ICD coding [8], [9]. Despite its potential, the integration of AI into EMRs presents several challenges, including data quality, system interoperability, and ethical concerns such as privacy, bias, and transparency [10], [11]. Healthcare professionals show varying acceptance levels, influenced by concerns over autonomy, workflow, and trust in AI [12], [13]. Regulatory and legal frameworks, particularly in developing countries, often lag behind technological advances [14].

While several bibliometric studies have broadly examined AI in healthcare and medicine [15], [16], only a few have focused on its application in EMR, and those were either limited in scope or based on outdated datasets [17]. To date, no comprehensive bibliometric mapping has specifically examined the convergence of AI and EMRs over the past decade. To address this gap, this study conducts a focused bibliometric review of AI integration in EMRs from 2015 to 2025. It highlights dominant themes, emerging applications, and research gaps—especially related to ethical issues, data security, and trust in AI systems. By mapping research trends and influential publications, this study contributes to shaping future research agendas and informing evidence-based policymaking in digital health and clinical informatics, with emphasis on underexplored areas crucial for responsible AI–EMR adoption. This study further contributes novelty by offering a comprehensive mapping of AI applications in EMRs across a broad, non–disease-specific landscape, introducing a thematic taxonomy derived from co-occurrence analysis, and systematically identifying research gaps that have not been addressed in previous domain-limited bibliometric reviews.

2. METHOD

This study used a quantitative descriptive design with bibliometric analysis to review literature on the convergence of AI and EMR. Bibliometric analysis, aided by topic-identification tools, offers quantitative insights into research output, trends, and thematic patterns over time [18]. Data were obtained from Scopus due to its broad coverage and inclusion of high-quality, peer-reviewed publications [19]. The search strategy used the keywords “electronic medical record” AND “artificial intelligence” in titles, abstracts, and keywords. The 2015–2025 range was selected to capture a decade of research that aligns with the rapid rise of AI adoption in healthcare, especially following the digital transformation accelerated by the COVID-19 pandemic [5], [6]. The search was conducted in March 2025. The keywords used for the data search are listed as follows: TITLE-ABS-KEY (“electronic medical record” AND “artificial intelligence”) AND PUBYEAR>2014 AND PUBYEAR<2026 AND (LIMIT-TO (SUBJAREA, “MEDI”) OR LIMIT-TO (SUBJAREA, “COMP”) OR LIMIT-TO (SUBJAREA, “ENGI”) OR LIMIT-TO (SUBJAREA, “HEAL”) OR LIMIT-TO (SUBJAREA, “NURS”) OR LIMIT-TO (SUBJAREA, “PHAR”) OR LIMIT-TO (SUBJAREA, “NEUR”) OR LIMIT-TO (SUBJAREA, “DECI”) OR LIMIT-TO (SUBJAREA, “SOCI”) OR LIMIT-TO (SUBJAREA, “BUSI”) OR LIMIT-TO (SUBJAREA, “DENT”) OR LIMIT-TO (SUBJAREA, “PSYC”) OR LIMIT-TO (SUBJAREA, “IMMU”)) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”)) AND (LIMIT-TO (PUBSTAGE, “final”)) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (LANGUAGE, “English”)).

Inclusion was limited to peer-reviewed English-language articles from journals and conference proceedings, while editorials, notes, book chapters, and non-English publications were excluded to maintain scientific quality and data consistency. This review relied exclusively on the Scopus database and focused on journal and conference articles published between 2015 and 2025 within medicine, computer science, engineering, health professions, and related subject areas. After screening, 681 documents were selected from 1,893 records. The diagram shows the search process adapted from Udin [18], as shown in Figure 1.

All retrieved documents from the final search query were included without additional title or abstract screening, following standard bibliometric practices emphasizing transparency, reproducibility, and minimal subjective judgment. Because the search strategy applied strict filters—publication year, subject area, document type, publication stage, and language—the resulting dataset was sufficiently refined to represent the AI–EMR research landscape. The entire set of 681 documents was therefore included in the analysis to avoid selection bias and ensure comprehensive mapping of research developments.

Data were analyzed using Microsoft Excel for publication trend analysis and VOSviewer (version 1.6.20) for keyword co-occurrence and thematic clustering. VOSviewer allows the visualization of bibliometric networks and facilitates the identification of conceptual structures in the dataset [20]. Keyword clustering was conducted through co-occurrence analysis of author-defined keywords to identify frequently associated terms and thematic groupings related to AI–EMR integration. A minimum occurrence threshold of 25 was applied to author-defined keywords to ensure that clustering reflected stable and meaningful patterns within the dataset while excluding infrequent terms that lacked analytical significance. The mapping workflow involved keyword-based retrieval using predefined search parameters, followed by bibliometric visualization and network analysis. Co-occurrence networks were used to form thematic clusters, citation metrics supported the identification of influential publications, and temporal overlay visualization illustrated the evolution of research attention across the decade.

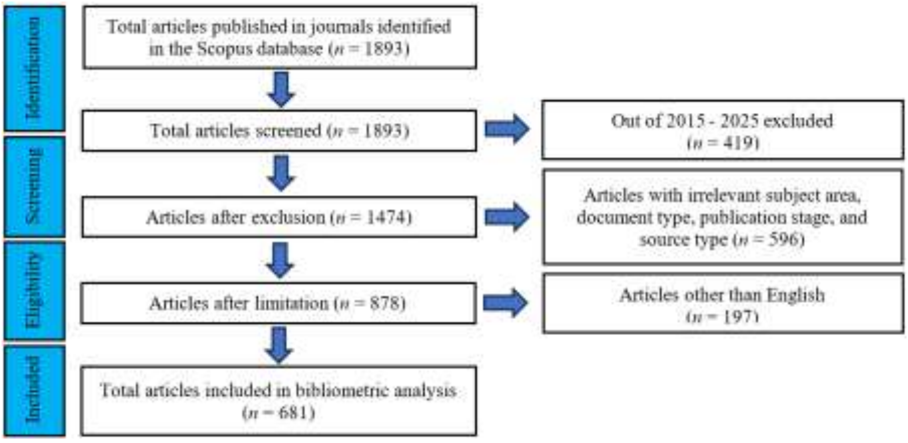


Figure 1. Steps in the identification and screening of sources

3. RESULTS AND DISCUSSION

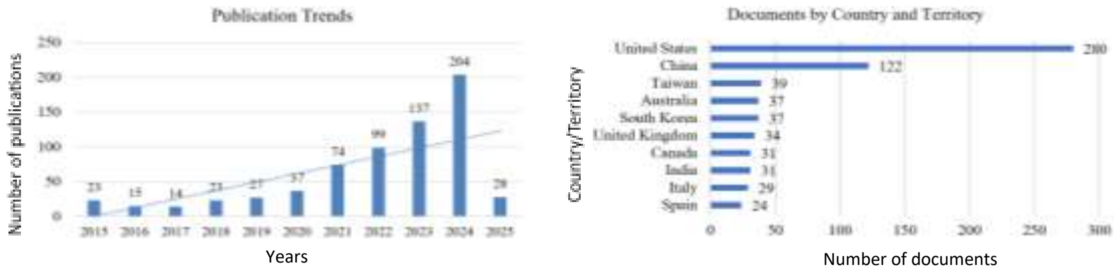
Figure 2 provides an overview of the temporal growth and geographical distribution of research on AI integration in EMR, illustrating how the field has evolved and where scholarly contributions are concentrated globally. A uniform yearly growth pattern in studies of AI in EMR has been observed, as shown in Figure 2(a). The concentration of studies on disease diagnosis suggests that AI–EMR integration is being prioritized in clinical decision-making tasks, reflecting its perceived value in enhancing diagnostic accuracy and efficiency [7]. Research on AI applications in EMR has gained much more attention over the last decade. This is driven by advancements in machine learning (ML) and deep learning (DL) technologies, which outperform conventional ML models and conventional data analysis techniques in the majority of clinical applications [21]. Adoption of EMR has increased as it improves healthcare delivery by enhancing data accessibility, reducing administrative burden, and improving operational efficiency and clinical documentation quality [22]. It is increased efficiency and precision demands for healthcare services also justify the adoption of the technology. The publication trend not only shows a steady rise in AI–EMR research but also illustrates a progressive shift toward more advanced methodological approaches, particularly DL models after 2020. The density and overlay visualizations complement this pattern by highlighting research concentrations around prediction, classification, and clinical decision-support tasks, enabling a clearer comparison of how thematic priorities evolve over time.

In addition to temporal growth, Figure 2 also highlights the global research landscape, allowing comparison of national contributions to this field. As illustrated in Figure 2(b), the majority of research and implementation efforts related to AI and EMR are concentrated in developed countries. These nations typically possess advanced IT infrastructures, high levels of interoperability, and comprehensive legal frameworks which safeguard the confidentiality of medical data [23]. In contrast, low-income countries often face significant challenges in EMR adoption, primarily due to budget constraints. Nevertheless, factors such as government support, public perception, and a culture of innovation play a crucial role in driving health sector advancements in these settings [24], [25].

China and India have significantly contributed to AI–EMR research through large-scale modernization of their healthcare systems, despite not being classified as developed countries. The COVID-19 pandemic accelerated China's adoption of 5G, big data, cloud computing, and AI, driven by government initiatives, despite persisting data quality and security challenges [26]. Similarly, India's expanding interest in AI–EMR research is driven by long-standing gaps in healthcare infrastructure, government efforts to build an economically accessible health system, and the growing need to leverage AI for early disease detection and large-scale data consolidation [27].

Several highly cited articles illustrate the impactful application of AI in clinical settings as shown in Table 1. Article by Hamet and Tremblay [28] has become a key reference for its thorough discussion of AI in medical decision-making and information management, along with it is exploration of social and ethical challenges associated with AI implementation in healthcare. Lundberg *et al.* [29] present a concrete application of ML for predicting hypoxemia during anesthesia, highlighting interpretable risk factors that enhance clinical trust. Similarly, Ker *et al.* [30] provide a comprehensive review of DL in medical image analysis, bridging technical and clinical perspectives and serving as a foundational reference for multidisciplinary researchers.

Kaissis *et al.* [31] address the critical issue of data privacy in AI-based medical imaging through federated learning and homomorphic encryption techniques, enabling secure data sharing in compliance with general data protection regulation (GDPR) and health insurance portability and accountability act (HIPAA) standards. Nemati *et al.* [32] developed an interpretable ML model for early sepsis prediction in intensive care units (ICUs) using EMR and physiological data, balancing high accuracy with clinical transparency. These widely cited studies highlight the importance of interpretability and clinical relevance in building trustworthy AI in healthcare.



(a) (b)

Figure 2. Research growth and global contribution in AI applied to EMR (a) annual publication trends and (b) documents by country and territory

Table 1. Top 5 most cited articles

No.	Author	Title	Journal	Year	Cited
1.	Hamet and Tremblay [28]	Artificial intelligence in medicine	Metabolism Clinical and Experimental	2017	1,481
2.	Lundberg *et al.* [29]	Explainable machine-learning predictions for the prevention of hypoxaemia during surgery	Nature Biomedical Engineering	2018	1,240
3.	Ker *et al.* [30]	Deep learning applications in medical image analysis	IEEE Access	2017	1,132
4.	Kaissis *et al.* [31]	Secure, privacy-preserving and federated machine learning in medical imaging	Nature Machine Intelligence	2020	736
5.	Nemati *et al.* [32]	An interpretable machine learning model for accurate prediction of sepsis in the ICU	Critical Care Medicine	2018	514

Research on AI and EMR is largely supported by health informatics and medical science organizations, reflecting multidisciplinary contributions as shown in Figure 3. These institutions require flexible ML platforms to handle clinical data effectively [33]. Information and communications technology industries also play a key role in funding AI-driven healthcare solutions. Technology developers, system designers, device manufacturers, and cloud providers play a key role in generating and managing data essential for health AI research [34]. Supported by public and private funding, researchers can advance algorithm-based systems to aid clinical decisions, enhance treatment effectiveness, and optimize EMR use for patient safety and efficiency [35].

Figure 3. Documents by funding sponsor

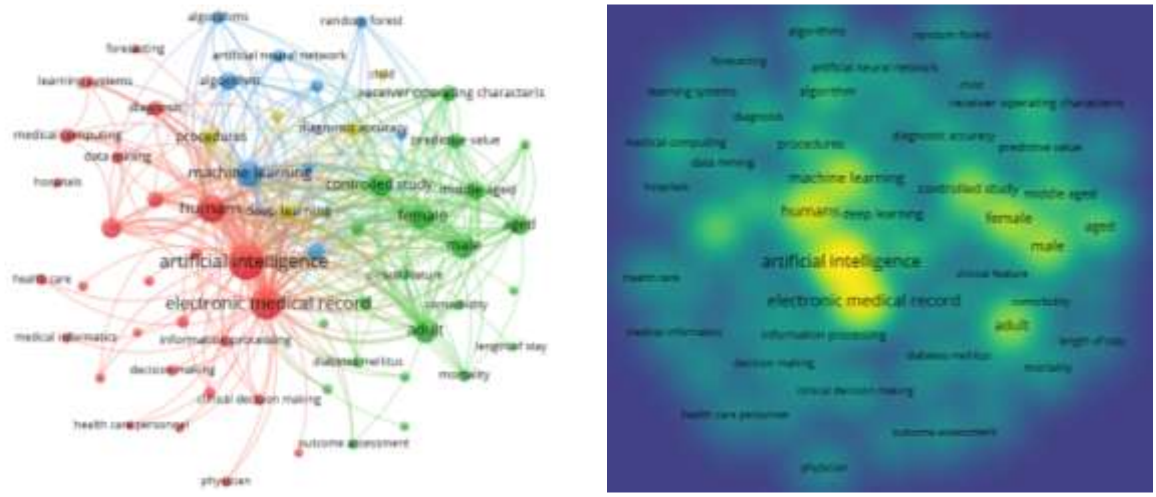
Figure 4 illustrates the conceptual structure and thematic intensity of research on AI in EMR derived from keyword co-occurrence analysis, enabling identification of dominant topics and their interrelationships within the literature. The word network visualization as shown in Figure 4(a) highlights key terms like artificial intelligence, machine learning, and procedures, reflecting a focus on precision in data management, diagnostic improvement, and data-driven decisions. Enhancing clinical data quality is crucial for producing reliable datasets that support research and medical solutions [36]. As healthcare systems become more integrated, managing AI-related risks requires coordinated efforts in data governance, assessment, and security [37]. The keywords are grouped into 4 clusters according to the theme of focus, as shown in Table 2. The clusters are represented in the colors red, green, blue, and yellow as shown in Figure 4(a).

The four clusters highlight key focus areas in the application of AI in EMR. The red cluster centers on integrating AI into healthcare systems for clinical decision-making and data management through tools like EMR and telemedicine. The green cluster focuses on patient demographics and clinical factors that influence treatment outcomes. The blue cluster emphasizes the use of ML algorithms and predictive models to enhance diagnostic accuracy. Lastly, the yellow cluster highlights the role of DL, particularly convolutional neural networks (CNNs), in improving diagnostic precision, especially in medical imaging and pediatric care. Across clusters, the prominence of DL architectures, random forests, and support vector machines (SVMs) reflects their central role in processing complex EMR data, aligning with current trends in clinically deployed AI systems. At the same time, recurring themes of privacy, transparency, and fairness highlight persistent ethical challenges that must be addressed to ensure safe, trustworthy, and accountable AI adoption within EMR environments. These patterns show that field is moving toward clinically actionable AI while simultaneously addressing the ethical requirements for responsible integration into healthcare systems. A clearer conceptual classification of AI in EMR research can be framed by data types, learning paradigms, and application domains. Integrating structured EMR data with unstructured clinical narratives has been shown to significantly improve predictive accuracy, including ICU mortality prediction, compared with using structured data alone [38]. Advances in natural language processing (NLP) and EMR mining also combine supervised and unsupervised methods, where unsupervised embeddings and semi-supervised vocabulary building reduce manual feature engineering, followed by supervised models for high-precision tasks such as allergy detection [39]. These methodological developments enable broader clinical and operational applications, from risk prediction and concept extraction to AI-enabled health information systems like EuCliD, which integrate automation and dynamic dashboards to improve efficiency across healthcare networks [40].

The density visualization as seen in Figure 4(b) highlights artificial intelligence, electronic medical record, humans, machine learning, female, and adult as the most prominent keywords, indicating a research focus on the application of AI-based data management to specific patient populations to enhance clinical decision-making accuracy. The density visualization functions as a heatmap surrogate, highlighting high-intensity zones dominated by DL and clinical decision-support topics. In parallel, citation metrics and network maps clarify which publications shape the field's development and how thematic areas interlink, providing a more comprehensive comparative view of research dynamics. This reflects the role of AI in personalized medicine, particularly in tailoring treatment decisions, predicting therapeutic responses, and assessing disease progression [7], [41]. In this context, key features like clinical guideline implementation, drug interaction alerts, and real-time decision support are crucial for enhancing the accuracy, safety, and efficiency of AI-driven clinical systems [42]. In contrast, keywords like health care personnel and physician appear less frequently, indicating limited focus on provider user experience despite their crucial role in EMR implementation. AI integration can enhance EMR usability and support seamless care transitions, making provider feedback essential for system development [43].

The presence of "hospital" and "health care" as frequent keywords, but the absence of "primary care", implies that AI and EMR research remains concentrated in hospital settings. This is notable given the potential of AI in primary care for improving disease screening, reducing provider burnout, and enhancing preventive care, though challenges like ethical concerns and the digital divide persist [44]. Central terms like artificial intelligence, machine learning, and deep learning indicate established themes, while peripheral terms such as random forest, algorithm, and artificial neural network point to underexplored areas. This gap opens opportunities for future research on AI algorithms, particularly long-short term memory (LSTM)-based DL models for temporal EMR data with improved interpretability and accuracy [45].

The overlay visualization in Figure 5 also illustrates the shifting research interests on AI and EMR over the past three years, indicated by the color transition from purple to turquoise, green, and yellow. Early research in 2021 focused on fundamental technologies which reflect the interest in system development. By mid-2021 to early 2022, research focused on AI usage. In mid-2022, the emphasis shifted towards clinical significance, showing growing interest in diagnostic accuracy. Through 2023, research interest continued even further to cover patient outcome prediction. This shift reflects a departure from system-oriented development toward practical AI applications to enhance patient care.



(a) (b)

Figure 4. Research themes and topic intensity in AI applied to EMRs (a) keyword network visualization and (b) keyword density visualization

Table 2. Clusters of keywords

Cluster	Color	Theme of focus	Keywords
1	Red	Application of AI in healthcare systems	AI, big data, clinical decision making, clinical decision support system, data analysis, data mining, decision making, diagnosis, electronic health record, EMR, EMR system, forecasting, health care, health care delivery, health care personnel, hospitals, humans, information processing, learning systems, medical computing, medical informatics, NLP, personalized medicine, physician, quality control, telemedicine, treatment outcome
2	Green	Patient characteristics and clinical assessment	Adult, aged, cardiovascular disease, clinical feature, comorbidity, demographics, diabetes mellitus, female, heart failure, hypertension, laboratory test, length of stay, male, middle aged, mortality, outcome assessment, predictive value, prognosis, receiver operating characteristic, risk assessment, very elderly
3	Blue	Predictive models and ML Algorithms	Algorithm, artificial neural network, decision tree, ML, prediction, predictive model, random forest, SVM
4	Yellow	DL techniques and diagnostic accuracy	Child, CNN, DL, diagnostic accuracy, procedures

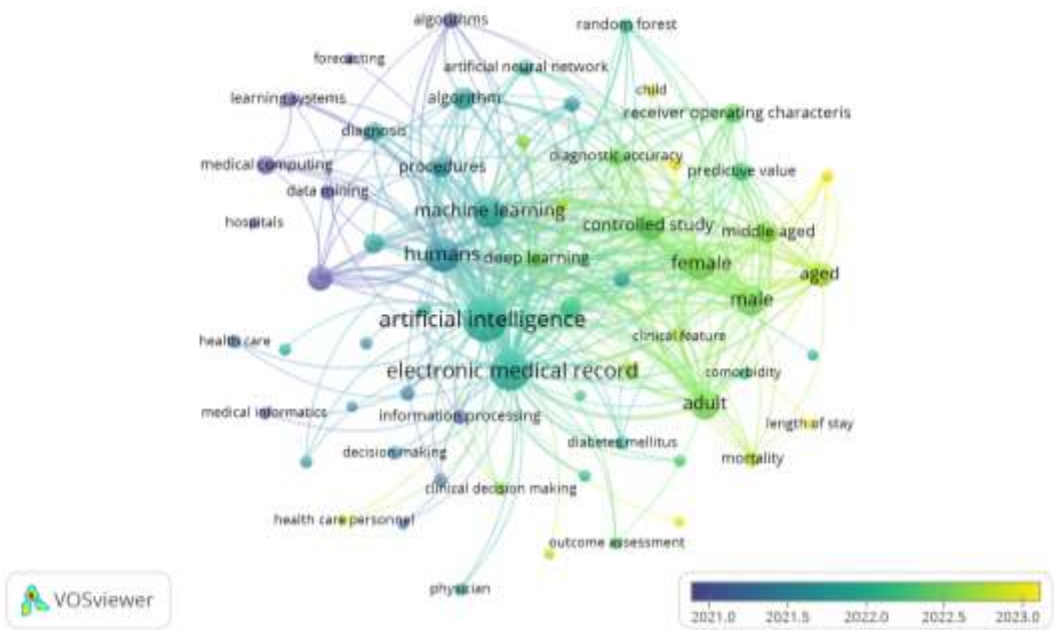


Figure 5. Overlay visualization

Recent studies further reinforce this transition by demonstrating notable progress in transformer-based models and real-world AI–EMR integration. Large clinical language models such as GatorTron, trained on extensive de-identified clinical text, have advanced core NLP tasks—concept extraction, natural language inference, and medical question answering—thus improving EMR interpretation of unstructured narratives [46]. Medical bidirectional encoder representations from transformers (Med-BERT) likewise enhances disease prediction by transferring pretrained contextual representations to structured EMR data, benefiting institutions with limited local datasets [47]. Alongside these advancements, privacy-preserving AI has become increasingly important, with federated and hybrid approaches enabling secure use of sensitive biomedical data without compromising patient confidentiality [48]. Advances in longitudinal patient modeling, including deep state-space methods, enhance predictive performance by capturing temporal patterns in clinical notes [49]. These developments support AI's expanding role in personalized care, where advanced models tailor treatment decisions, anticipate therapeutic responses, and integrate complex clinical histories to reveal evolving risk profiles often missed in routine assessments [7], [41]. Complementing these methodological innovations, recent reviews highlight expanding applications of AI and GenAI within EMR platforms to improve data handling, clinical prediction, communication, and workflow efficiency [50]. Collectively, these advancements contribute to population health management and early disease identification, as demonstrated by AI–EHR models that can streamline patient selection, enhance surveillance, and accelerate early diagnosis across hospital systems [51], [52].

Beyond algorithmic developments, several systemic challenges continue to limit the adoption of AI in EMR environments. Data heterogeneity remains a key challenge, as conventional integration methods struggle to unify complex clinical data, increasing the need for advanced AI-driven solutions to ensure reliable analytics [53]. Annotation workflows also face constraints, since even with emerging LLM-based annotation agents, issues such as quality assurance, bias, and transparency persist and hinder the creation of dependable large-scale clinical datasets [54]. AI models also often fail to generalize across institutions due to varying patient populations and regulatory constraints, requiring site-specific adaptations or transfer learning to maintain performance [55]. These technical challenges are further intensified by strict data protection regulations, which require privacy-preserving methods such as federated learning and differential privacy to meet HIPAA and GDPR standards [56]. Difficulties in aligning AI tools with clinical workflows and existing EHR systems also hinder implementation, especially amid persistent real-world data inconsistencies and interoperability gaps [57], [58].

This study examines the convergence of EMR and AI research on the foundation of systematic bibliometric analysis of the Scopus database over the past ten years. The strongest aspect of this research is its use of bibliometric analysis, which provides rapid yet broad insight into trends in research and future opportunities for innovation. However, this study is limited by the use of a constrained keyword set, which may not fully capture all relevant issues related to AI and EMR, and its focus on publication numbers rather than quality or depth of research. Hence, important contributions with fewer citations might be left out. It requires overcoming such limitations through more research that is focused on some areas of AI implementation within EMR to enhance knowledge and spur innovation within this field.

4. CONCLUSION

This study provides a comprehensive bibliometric mapping of AI–EMR research from 2015 to 2025, revealing a steady growth in scholarly output and highlighting four major thematic areas: AI-driven healthcare delivery, patient-related factors, predictive ML models, and the expanding role of DL in diagnostic enhancement. Despite this progress, significant gaps remain, particularly in primary care implementation, involvement of healthcare personnel, and the development of interpretable and domain-specific algorithms, alongside persistent concerns related to privacy, trust, and ethical deployment. By presenting a broad, non–disease-specific synthesis, introducing a thematic taxonomy derived from co-occurrence analysis, and systematically identifying structural research gaps, this study offers a novel contribution that supports evidence-based policymaking and responsible AI–EMR integration. Future work may advance this foundation through real-time EMR analytics, patient-centered AI architectures, and cross-border data harmonization, complemented by more granular bibliometric or topic-modeling techniques to capture emerging subfields and contextual applications.

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AUTHOR CONTRIBUTIONS STATEMENT

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Merita Arini	✓	✓		✓			✓			✓		✓		

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

The authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study were obtained from the Scopus database. The dataset was generated through a defined search strategy using the keywords “electronic medical record” AND “artificial intelligence” for publications between 2015 and 2025. Due to Scopus licensing restrictions, the raw data cannot be publicly shared; however, all search queries, inclusion criteria, and analysis procedures are described in this article to ensure transparency and reproducibility. Researchers with access to Scopus may replicate the dataset using the same search parameters.

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