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REVIEW **Open Access**

Research trends and ethical perspectives on explainable artificial intelligence in emergency medicine: a bibliometric analysis

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Abstract

Background Explainable artificial intelligence (XAI) has become increasingly relevant for ensuring transparency, interpretability, and trust in clinical decision support systems. In emergency medicine, where decision-making is time-critical and data are often incomplete, XAI provides significant opportunities while also raising ethical and methodological challenges. Despite the rapid growth of AI applications in acute care, bibliometric studies explicitly integrating explainability and ethics remain limited.

Methods A bibliometric analysis of 433 publications on XAI in emergency medicine was conducted using the Web of Science Core Collection. The search covered 1986 through November 2025 and included peer-reviewed research articles and reviews in English related to *emergency medicine*, *artificial intelligence*, *explainability*, and *ethics*. Bibliometric indicators (publication trends, citation counts, journals, authors, and countries) were analyzed using Bibliometrix (R), while VOSviewer was used to visualize thematic clusters and keyword co-occurrence. Citations were analyzed as cumulative counts up to November 2025 and normalized to per-publication counts per year.

Results Research output increased sharply after 2018, peaking in 2023 with approximately 90 publications, reflecting the growing focus on interpretability and transparency in emergency care. Cumulative citations exceeded 1,400 by 2025. The United States, the United Kingdom, and China were the most productive countries. Annals of Emergency Medicine, NPJ Digital Medicine, and BMJ Open were the most influential journals, while Ong M.E.H., Dwivedi G., Stewart J., Wang Y., and Li J. emerged as leading contributors. Thematic mapping revealed four major clusters: (1) methodological development of interpretable models, (2) clinical applications in triage, imaging, and sepsis risk prediction, (3) ethical and human-factor dimensions (bias, accountability, transparency), and (4) emerging topics such as large language models. Despite rapid progress, most studies remained retrospective and lacked standardized interpretability metrics, multicenter validation, and consistent reporting of explainability outputs.

Conclusion Research on XAI in emergency medicine is expanding rapidly and is increasingly shaped by a small group of influential journals and authors. However, critical gaps remain, including the limited availability of prospective studies, insufficient clinician involvement, and ethical frameworks that are not yet fully tailored to emergency settings. Addressing these gaps through multidisciplinary collaboration, standardized evaluation metrics, and stronger governance will be important to support transparency, accountability, and the safe clinical adoption of XAI in emergency medicine.

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Keywords Explainable artificial intelligence, Emergency medicine, Bibliometric analysis, Ethics, Machine learning, Clinical decision support

Introduction

Artificial intelligence (AI) is rapidly reshaping healthcare by enhancing diagnostic accuracy, improving prognostication, and streamlining clinical workflows. Emergency medicine represents one of the most critical domains for these advances. Characterized by high patient turnover, limited prior information, and severe time pressure, emergency departments (EDs) provide a setting in which AI's speed, scalability, and pattern recognition capacity can yield substantial clinical benefits [1]. However, in such high-stakes environments, clinical applicability depends not only on accuracy but also on the transparency and interpretability of algorithmic outputs. The need for explainable artificial intelligence (XAI) arises from the requirement that physicians must understand, verify, and trust the rationale behind model predictions before applying them in patient care.

Explainability refers to the degree to which humans can understand a model's internal logic, whereas interpretability describes how specific input features influence a model's decision [2, 3]. These properties ensure that AI serves as a supportive decision aid—rather than an opaque "black box"—within time-sensitive emergency workflows.

Recent studies have highlighted the potential of artificial intelligence to predict critical care requirements in prehospital settings [4], identify major adverse cardiac events in emergency department chest pain patients [5], and forecast cardiac arrest using electrocardiography data [6]. For example, explainable triage systems integrating SHapley Additive exPlanations (SHAP) visualizations have been shown to improve clinician confidence by revealing how vital signs, age, and triage category influence admission risk [7]. Similarly, interpretable sepsis early-warning models highlight the most influential laboratory and physiological parameters triggering alerts, facilitating timely intervention, and supporting clinical accountability [8]. In diagnostic imaging, saliency-based deep learning models applied to chest radiographs have demonstrated both high accuracy and transparent reasoning, enabling radiologists and emergency physicians to validate automated findings rapidly [9, 10]. Collectively, these findings illustrate the direct clinical relevance of explainable AI approaches.

Beyond emergency care, AI has been recognized as a transformative framework in global healthcare delivery. Early contributions emphasized its potential to revolutionize diagnostics, decision-making, and patient monitoring [11], while more recent analyses highlight its role in building sustainable, data-driven health systems worldwide [12]. In clinical practice, AI is now applied across diverse domains, ranging from imaging and triage to predictive modeling and personalized care [13].

Within emergency medicine specifically, promising results have been reported not only in triage and mortality prediction but also in imaging interpretation (CT, chest radiographs), electrocardiogram (ECG) analysis, and sepsis early warning systems [8, 14]. Narrative reviews suggest that natural language processing (NLP) models, which leverage free-text triage notes, can predict admission, triage category, and critical illness with high accuracy, often outperforming approaches that use only structured data. However, most of these studies remain retrospective and are at high risk of bias [15]. Complementary systematic and scoping reviews confirm the growing momentum of AI in emergency medicine, with increasing emphasis on explainability, trust, and workflow integration [16–18]. At the same time, the integration of AI into acute care presents both opportunities and challenges, spanning methodological, operational, and ethical dimensions [19, 20].

The ethical and social implications of AI in healthcare have become increasingly prominent. Bibliometric analyses demonstrate a sharp rise in publications since 2018, peaking in 2023, with citations exceeding 900 by 2025 [21]. Recurring themes include ethics, machine learning, privacy, bias, transparency, and accountability, with the United States, United Kingdom, and Switzerland identified as leading contributors. Reviews further emphasize that ethical concerns cluster around six domains: privacy, individual autonomy, bias, responsibility and liability, evaluation and oversight, and the evolving roles of healthcare professionals [22].

In the context of emergency medicine, these debates are particularly complex. Although emergency physicians possess strong clinical expertise, most lack formal training in AI, and many models are perceived as "black boxes," undermining trust and adoption [1]. Explainable artificial intelligence (XAI) has therefore emerged as a critical framework for making model outputs transparent, interpretable, and verifiable. Arrieta et al. and Amann et al. emphasized that XAI is indispensable for trustworthy AI in healthcare, requiring ethical, legal, and social safeguards [2, 3]. Recent pilot studies using large language models (e.g., ChatGPT, Gemini) in triage and documentation further underscore both their potential and associated safety concerns, highlighting the need for explainability and rigorous validation in ED contexts [23–25]. Notably, concerns have also been raised about the reliability of chatbots in adhering to resuscitation guidelines, reinforcing the importance of explainability in high-stakes emergency care [26].

This study offers bibliometric insights into the evolution, thematic structure, and ethical considerations of XAI research in emergency medicine. While prior reviews have examined general applications of AI in acute care, none have systematically mapped the intersection of bibliometric trends and ethical dimensions of explainability. By combining quantitative bibliometric techniques with qualitative insights into ethical debates, this study provides a novel, multidimensional perspective that not only charts research productivity but also identifies critical gaps in the responsible adoption of AI. This dual emphasis enhances the relevance of the study's findings for both researchers and clinicians seeking to strike a balance between innovation and accountability in high-stakes emergency settings.

Materials and methods

This study conducted a bibliometric analysis to examine the scientific evolution of explainable artificial intelligence (XAI) research in emergency medicine. All bibliographic records were retrieved from the Web of Science (WoS) Core Collection, which was selected for its indexing of high-quality peer-reviewed journals, standardized metadata, and comprehensive citation information.

A three-stage search strategy was employed to capture the full scope of research on artificial intelligence, ethics, and explainability in emergency medicine. All searches were performed on 12 November 2025 using the WoS Topic Search (TS) field.

The first search was designed to identify the broadest spectrum of artificial intelligence applications in emergency medicine. The query was:

TS = ("emergency medicine" OR "emergency department" OR "ED") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "ChatGPT" OR "GPT-3" OR "GPT-4" OR "large language model" OR "LLM" OR "explainable artificial intelligence" OR "explainab" OR "interpretab" OR "interpretable model" OR "explainable model" OR "transparent" OR "SHAP" OR "LIME" OR "saliency" OR "prototype learning" OR "trustworthy AI" OR "model interpretability").

This comprehensive search yielded 4,680 records, providing an overview of AI-related literature in emergency medicine.

To identify literature addressing ethical, legal, fairness-related, and governance issues linked to AI in emergency medicine, a second exploratory search was conducted:

TS = ("emergency medicine" OR "emergency department" OR "ED") AND (ethic* OR liability OR responsibility OR accountability OR bias OR fairness OR privacy OR "data security" OR governance OR transparency).

This search yielded 3,498 records, representing the ethical and governance-oriented AI literature in emergency care.

The analytical corpus was constructed using a more restrictive search that required the simultaneous presence of terms related to emergency medicine, artificial intelligence, and explainability. The final query was:

TS = ("emergency medicine" OR "emergency department" OR "ED") AND ("ethic" OR "liability" OR "responsibility" OR "accountability "OR "bias" OR "fairness" OR "privacy" OR "data security" OR "governance" OR "transparency") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "ChatGPT" OR "GPT-3" OR "GPT-4" OR "large language model" OR "LLM" OR "explainable artificial intelligence" OR "explainab" OR "interpretab" OR "interpretable model" OR "explainable model" OR "transparent" OR "SHAP" OR "LIME" OR "saliency" OR "prototype learning" OR "trustworthy AI" OR "model interpretability").

This targeted search yielded 433 unique publications, which constituted the final analytic dataset.

Inclusion and exclusion criteria

The initial search retrieved 433 records published between 1986 and 2025. Eligible studies met the following criteria:

- peer-reviewed journal articles or reviews,
- written in English,
- directly related to emergency departments, emergency care, critical care, triage, or prehospital/EMS settings where AI/XAI was applied.

The following were excluded:

- conference abstracts, editorials, letters, and corrections;
- veterinary or non-human studies;
- records unrelated to artificial intelligence despite terminological overlap.

Data analysis

Descriptive statistics (publication year, author affiliations, countries, journals, and citation counts) were analyzed using the Bibliometrix package in R [20]. Keyword co-occurrence analysis was conducted using VOSviewer [21], which enabled the visualization of thematic clusters. Thematic mapping further categorized research into motor, niche, basic, and emerging/declining themes based on centrality and density. Bradford's law was applied to identify the core set of journals contributing the highest publication volumes.

Ethical considerations

As this study relied solely on bibliographic data from a publicly available database and did not involve human or animal participants, institutional ethical approval was not required.

Results and discussion

Publication trends and citation impact

Research on explainable artificial intelligence (XAI) in emergency medicine remained limited until the mid-2010s but accelerated rapidly after 2018, marking a clear inflection point in the field's scientific trajectory.

Annual publication output increased from fewer than 10 papers per year before 2015 to nearly 90 publications by 2023, reflecting the growing emphasis on interpretability, transparency, and trustworthiness in AI-driven clinical decision-making (Fig. 1).

To ensure temporal completeness, the current analysis spans 1986–2025, thereby capturing early conceptual contributions and methodological frameworks that helped shape explainability research. This time window aligns the narrative with Fig. 1, which depicts annual publication counts alongside cumulative citation growth over time.

Citation activity mirrored this expansion. The normalized citation rate—defined as citations per publication per year—rose sharply after 2018, indicating that a rise in scholarly impact accompanied the surge in publication volume. By 2025, cumulative citations surpassed 1,400, suggesting that explainable AI research in emergency medicine has transitioned from exploratory theoretical discussions to clinically validated and translational applications.

Comparable bibliometric dynamics have been documented in other healthcare AI domains, where explainability and interpretability emerged as dominant research priorities [19, 20, 27]. This trend coincides with emergency medicine's reliance on high-velocity, multimodal, and time-critical data streams, making it an ideal context for deploying interpretable machine learning models that balance predictive accuracy with clinical transparency [9, 17, 28].

Clinical evidence substantiates this bibliometric evolution. Multiple studies have demonstrated the potential of AI and XAI frameworks to predict critical care needs in prehospital triage [4], identify major adverse cardiac events in emergency chest pain cohorts [5], and forecast cardiac arrest using electrocardiography (ECG)-based predictive models [6]. Collectively, these findings suggest that XAI has evolved into a mature, applied translational paradigm that is shaping modern emergency medicine.

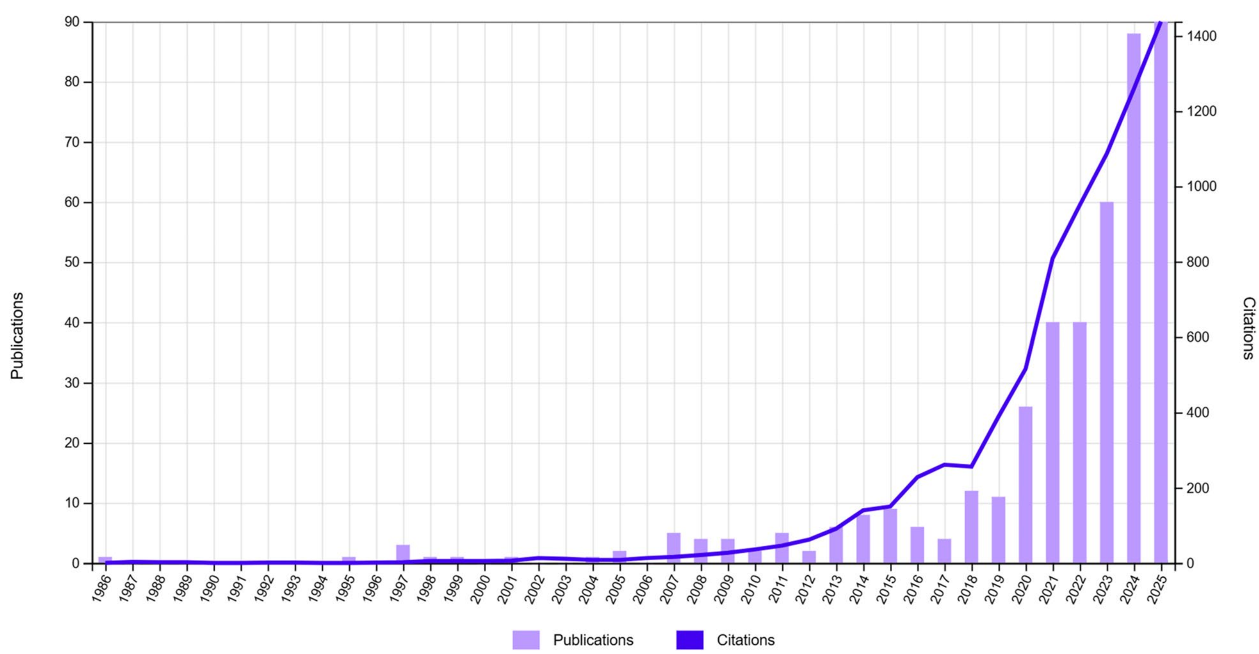

Fig. 1 Annual trends in publication and citations related to explainable artificial intelligence (XAI) in emergency medicine

Research life cycle and growth forecast

The logistic growth modeling (Fig. 2a–b) suggests that research on explainable artificial intelligence (XAI) in emergency medicine follows a classic S-shaped trajectory, which is commonly observed in expanding scientific domains. The annual publication curve (Fig. 2a) shows a steep rise beginning in 2018, consistent with the broader increase in interest in interpretable and trustworthy AI. The fitted model shows a strong goodness of fit ($R^2 = 0.974$) and projects a potential publication peak around 2028, followed by a gradual slowing as the field matures. These projections should be interpreted as scenario-based estimates that are sensitive to model assumptions, database updates, and evolving terminology.

The cumulative growth curve (Fig. 2b) supports this maturation pattern, indicating a move from rapid expansion toward consolidation. The model projects an eventual saturation on the order of 1,640 cumulative publications, with an inflection point reached between 2023 and 2024. As with any growth model, these values are not deterministic forecasts; they are best viewed as a quantitative summary of recent dynamics that may shift with changes in funding, regulation, and the adoption of generative AI in emergency workflows.

Taken together, the life-cycle results imply that while publication volume may slow after the late 2020s, the field's importance is likely to persist through methodological refinement, clinical implementation studies, and ongoing ethical and governance work. Future contributions may increasingly emphasize prospective validation, standardization of interpretability metrics, and operational integration in emergency settings.

Citation landscape

The citation analysis revealed that scholarly influence in explainable artificial intelligence (XAI) and emergency medicine is highly concentrated within a small subset of seminal contributions. Both global and local citation networks were systematically evaluated to identify the most influential studies, with normalization metrics—citations per publication per year and normalized citation index—applied to ensure comparability and temporal balance (Fig. 2a–b).

At the global level, the citation hierarchy is dominated by foundational and methodological publications that established the conceptual and ethical frameworks of XAI in healthcare.

The most globally cited article was *Moons* et al. (2015, *Annals of Internal Medicine*, https://doi.org/10.7326/M14-0698), which received 2,557 citations and achieved a normalized citation index of 8.52, representing a landmark in model transparency and reporting standards for clinical prediction research.

Other highly influential works include *Baggs* et al. (2011, *Pediatrics*, TC = 246), *Supran* et al. (2021, *One*

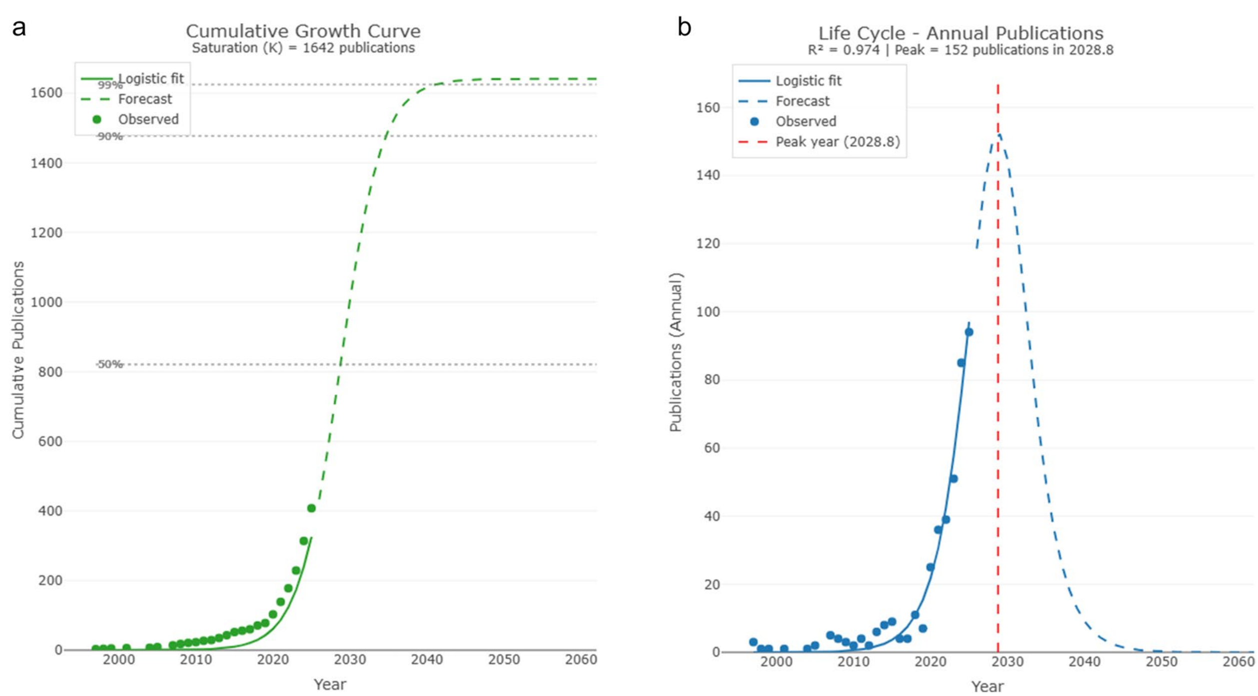

Fig. 2 **a** Research life-cycle modeling and citation landscape of XAI in emergency medicine

Earth, TC = 227), and *Lee* et al. (2018, *NPJ Digital Medicine*, TC = 211).

Although these studies extend beyond emergency medicine, they remain pivotal to the interdisciplinary discourse that anchors explainability, accountability, and reproducibility in contemporary clinical data science.

By contrast, the local citation landscape, which captures intra-domain influence within emergency medicine, reveals a more application-driven and translational research structure.

The most locally cited papers include *Stewart* et al. (2018, *Emergency Medicine Australasia*, LC = 4, GC = 107), *Kachman* et al. (2024, *American Journal of Emergency Medicine*, LC = 3, GC = 17), and *Okada* et al. (2023, *Clinical and Experimental Emergency Medicine*, LC = 2, GC = 23).

While these studies have comparatively modest global visibility, their local citation density (mean = 12.3 citations per publication per year) highlights their immediate clinical relevance to emergency-specific model validation, triage optimization, and the ethical deployment of interpretable algorithms.

This duality—the conceptual dominance of global methodological frameworks and the practical influence of locally applied studies—illustrates a maturing research ecosystem.

Global leaders such as *Moons*, *Lee*, and *Supran* established the theoretical and ethical scaffolding of XAI, whereas domain-specific contributors, including Stewart, Okada, and Kachman, have translated these frameworks into real-world emergency decision-support systems.

Collectively, these findings suggest that the intellectual structure of XAI in emergency medicine remains pyramidal—with a narrow apex of highly cited conceptual foundations supporting a rapidly expanding base of contextual, application-oriented investigations.

This synergy between global theory and local implementation mirrors patterns observed in radiology and critical care research, reinforcing XAI's growing translational maturity and clinical integration within acute care medicine.

Journals and scholarly influence

The distribution of publications across journals underscores the interdisciplinary yet selective nature of explainable artificial intelligence (XAI) research in emergency medicine. As presented in Table 1, the Annals of Emergency Medicine emerged as the most influential source, with six publications and the highest total citation count (TC = 144; *h*-index = 6), reaffirming its position as a leading clinical outlet that bridges innovation with emergency care practice.

In contrast, NPJ Digital Medicine demonstrated the most substantial normalized citation impact, averaging 82.5 citations per publication, despite contributing only four papers. This pattern reflects the journal's central role in advancing methodological and conceptual frameworks for interpretable artificial intelligence in clinical medicine. Its prominence within the Bradford core zone highlights how high-impact interdisciplinary outlets continue to shape the theoretical underpinnings of XAI adoption.

Among generalist and multidisciplinary platforms, PLOS One (*NP = 7, TC = 165*) and JAMA Network Open (*NP = 4, TC = 72*) exhibited substantial engagement, reflecting the growing diffusion of explainability-centered research into mainstream biomedical publishing. Similarly, BMJ Open (*NP = 10, TC = 33*) and the Journal of Surgical Education (*NP = 14, TC = 36*) contributed significantly to applied and educational perspectives, emphasizing translational readiness and clinician-focused training on AI tools.

Traditional emergency medicine journals—including the American Journal of Emergency Medicine (*NP = 8, TC = 66*), Academic Emergency Medicine (*NP = 6, TC = 35*), and the Canadian Journal of Emergency

Table 1 Core journals and citation metrics of explainable ai research in emergency medicine

Source	*h-index*	*g-index*	*m-index*	*TC*	*NP*	*PY_start*	*CPP*
Annals of Emergency Medicine	6	6	0.43	144	6	2012	**24.0**
NPJ Digital Medicine	4	4	0.50	330	4	2018	**82.5**
PLOS One	4	7	0.31	165	7	2013	**23.6**
JAMA Network Open	4	4	0.67	72	4	2020	**18.0**
Journal of Surgical Education	4	5	1.00	36	14	2022	**2.6**
BMJ Open	3	5	0.43	33	10	2019	**3.3**
American Journal of Emergency Medicine	3	8	0.50	66	8	2020	**8.3**
Academic Emergency Medicine	3	5	0.30	35	6	2016	**5.8**
Canadian Journal of Emergency Medicine	3	5	0.50	57	5	2020	**11.4**
Emergency Medicine Australasia	3	4	0.19	219	4	2010	**54.8**

Medicine (*NP = 5, TC = 57*)—showed steady adoption of interpretable AI frameworks. Although their mean citation rates remain lower than those of digital health–oriented journals, their inclusion in the Bradford core zone confirms that XAI research has transitioned from an experimental focus toward mainstream emergency practice.

Collectively, these patterns illustrate that scholarly influence in XAI-related emergency research remains unevenly distributed yet progressively diversifying. While a small group of high-visibility journals continues to dominate citation impact, the growing representation of traditional emergency outlets signals a structural shift—where explainability, transparency, and accountability are becoming integral to the publication standards of clinical and educational research alike.

Authors and intellectual core

Authorship analysis revealed a highly collaborative and globally distributed research network, reflecting the multidisciplinary nature of explainable artificial intelligence (XAI) in emergency medicine. Across 433 documents, 2,734 distinct authors contributed, with an average of 6.7 co-authors per paper and 24.2% international collaboration, indicating that cross-institutional partnerships are a key driver of progress in this field.

As shown in Fig. 3a, *Li J* and *Wang Y* emerged as the most prolific authors, each contributing five papers, followed by *Dwivedi G*, *Lee S*, *Ong M.E.H.*, and *Stewart J* with four publications each.

When adjusted for fractional authorship, *Wang Y* (*FA = 0.85*) and *Ong M.E.H.* (*FA = 0.76*) had the strongest normalized productivity, indicating sustained engagement in both methodological development and the clinical implementation of interpretable models.

The local citation network (Fig. 3b) highlights *Dwivedi G*, *Ong M.E.H.*, *Sprivulis P.*, and *Stewart J* as the most influential contributors within emergency medicine, each receiving five local citations. These authors have been instrumental in bridging the conceptual frameworks of machine-learning explainability and operational emergency-care analytics. Notably, Dwivedi G and Stewart J have led multi-site collaborations on AI-based risk stratification, while Ong M.E.H. has played a central role in developing interpretable triage algorithms and decision-support systems deployed in emergency departments across the Asia–Pacific region.

Global impact metrics (Fig. 3c) mirror this trend: high-citation papers authored by *Wang Y* (Advanced Theory and Simulations, 2024; TC = 9), *Li J* (*BMC Nursing*, 2025; TC = 0, emerging citation trajectory*), and *Vassar M* (*European Heart Journal*, 2025; TC = 2*) underscore the breadth of interdisciplinary engagement, spanning health informatics, policy, and applied clinical research. Despite relatively modest citation counts for 2024–2025 papers due to their recency, their rapid accumulation of attention indicates accelerated scholarly diffusion.

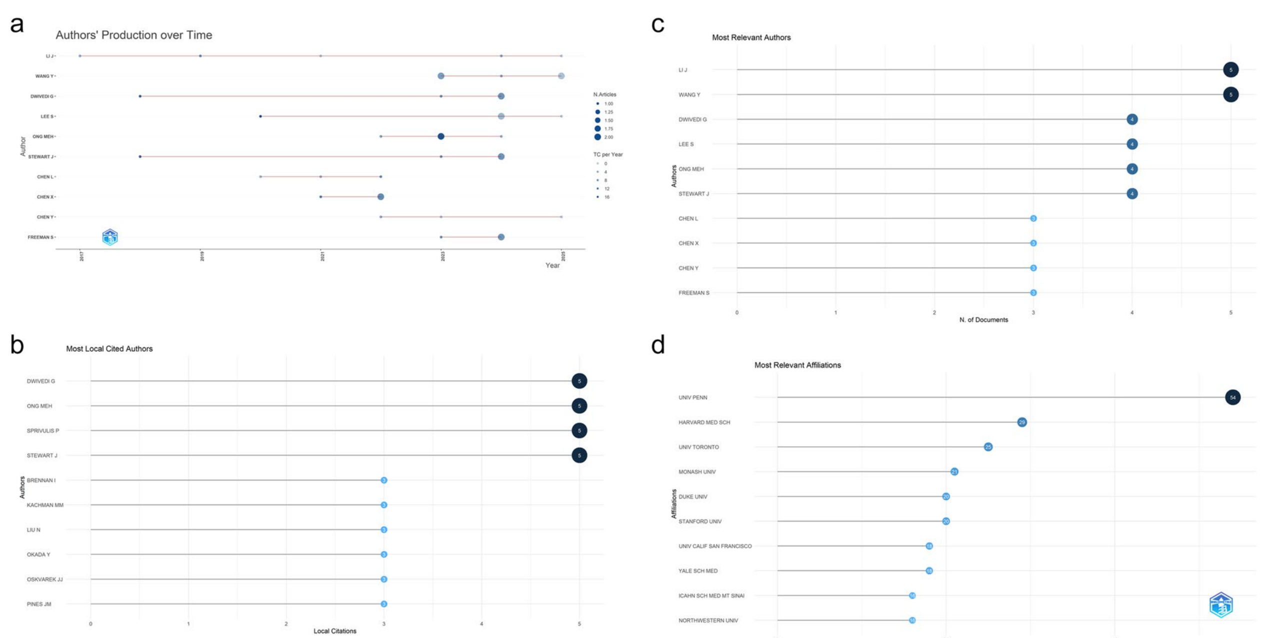

Fig. 3 **a** Most relevant authors. **b** Most local cited authors. **c** Most relevant authors **d** Institutional co-authorship network

Institutional co-authorship mapping revealed that the University of Pennsylvania (58 articles), Harvard Medical School (30), the University of Toronto (25), Duke University (22), and Monash University (21) are the principal centers of production (Fig. 3d). These hubs form the core of an international collaboration network extending across North America, Europe, and the Asia–Pacific region. Their dominance reflects long-standing expertise in emergency-care informatics and data-driven clinical decision support.

Taken together, these findings demonstrate that the intellectual core of XAI in emergency medicine remains anchored by a small but globally interconnected group of scholars and institutions who are translating machine-learning interpretability into actionable, ethically grounded clinical applications. While the field continues to diversify, its leadership structure remains cohesive, ensuring methodological rigor and continuity across domains.

Thematic and keyword structures

Thematic mapping of the literature identified four principal domains that define the conceptual landscape of XAI in emergency medicine (Fig. 4). Motor themes—including *machine learning*, *artificial intelligence*, and *emergency department applications*—constitute the intellectual and practical core of the field, underscoring their pivotal role in methodological innovation and clinical translation [1].

Niche themes, such as *quality improvement*, *governance*, and *policy transformation*, represent specialized but less interconnected areas, often reflecting targeted investigations on patient safety, healthcare quality, and institutional implementation that remain peripheral to mainstream emergency workflows [29].

Basic themes, encompassing *education*, *clinical decision-making*, and *neural networks*, remain broadly relevant but are insufficiently integrated, highlighting opportunities to deepen the adoption of explainable models in day-to-day emergency department practice. Finally, emerging or declining themes, including *federated learning*, *computer vision*, and *mental health*, reflect areas of methodological experimentation; some are poised to mature into stable research paradigms, while others may lose prominence as the field consolidates [30, 31].

Keyword co-occurrence analysis supported these findings, revealing four dominant thematic clusters (Fig. 5). The first cluster reflects methodological

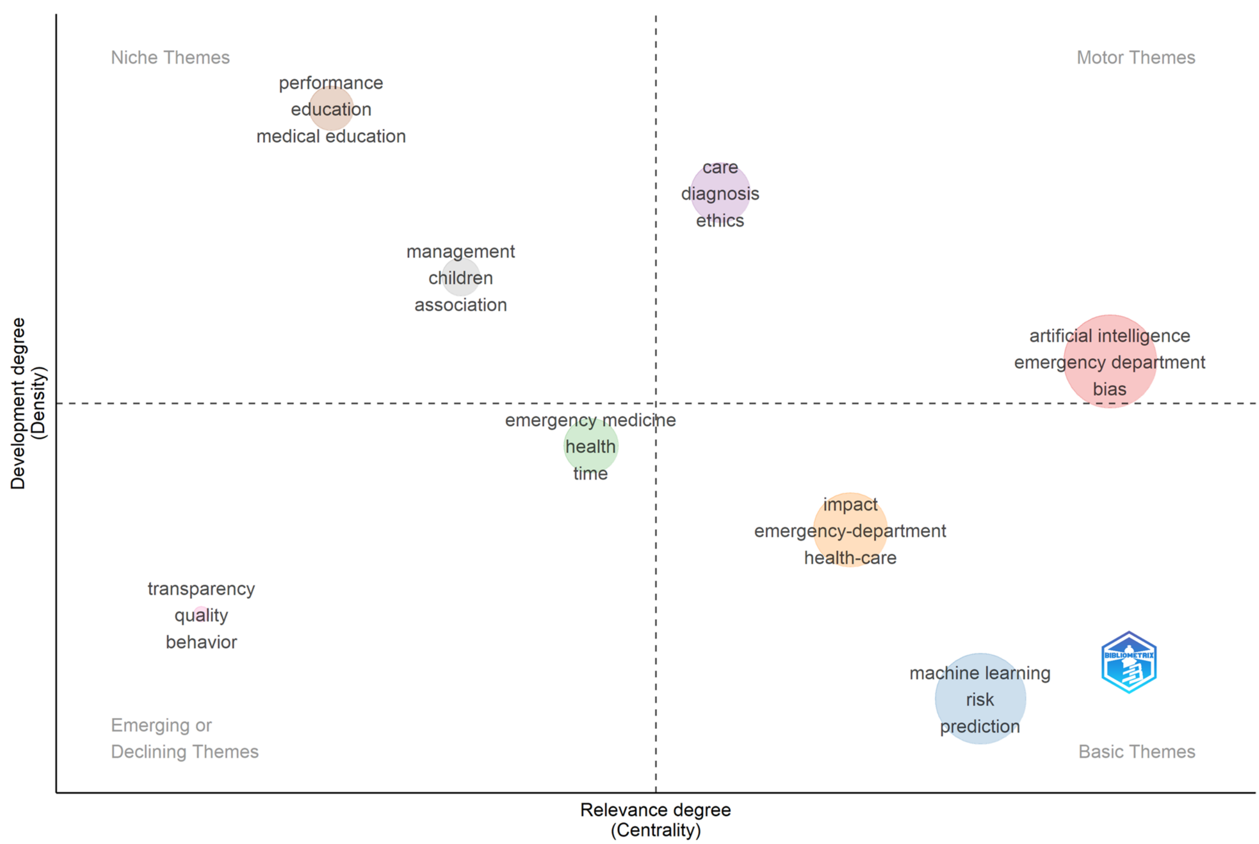

Fig. 4 Thematic map of publications on explainable artificial intelligence in emergency medicine

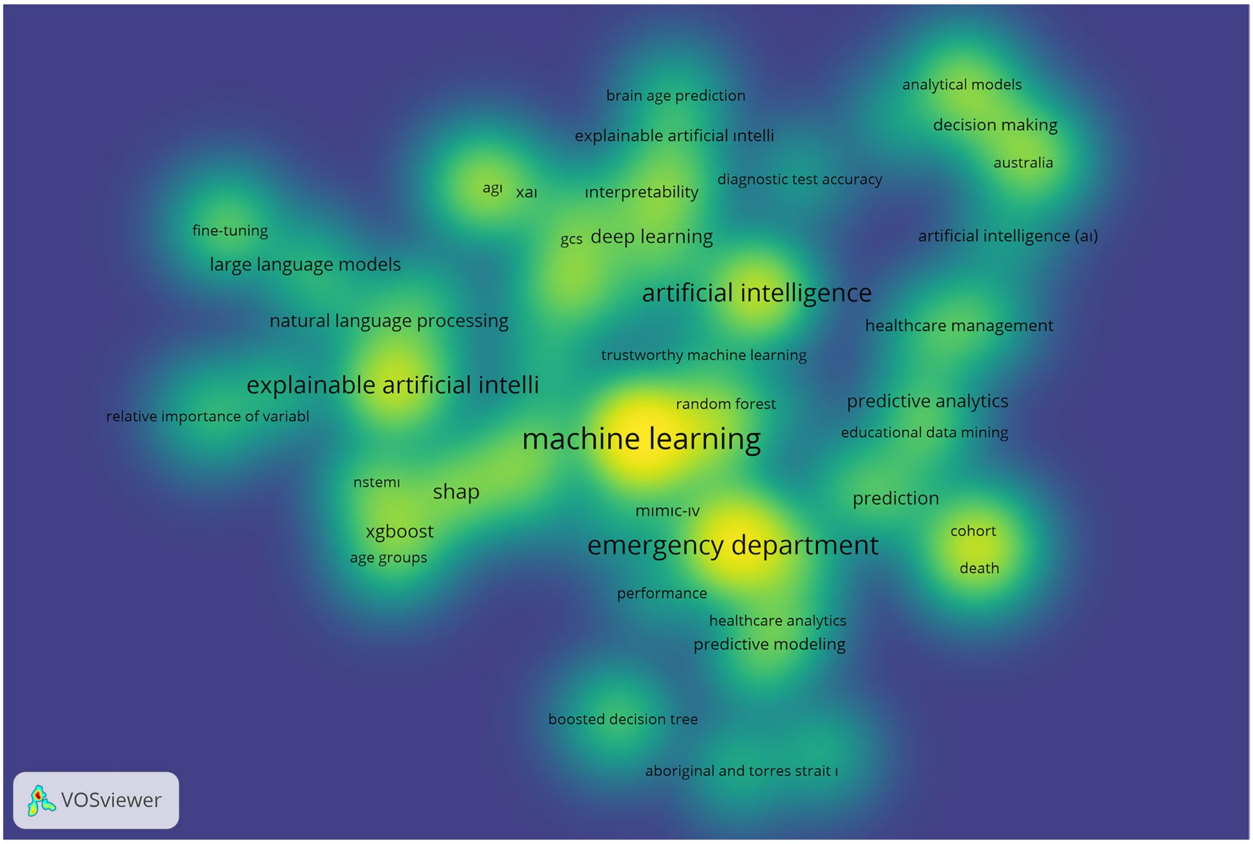

Fig. 5 Keyword co-occurrence network in explainable artificial intelligence (XAI) research within emergency medicine, illustrating major thematic clusters

advances, including SHAP, LIME, AutoScore, and other interpretable machine learning models that form the technical foundation of XAI [2, 3]. The second cluster highlights clinical implementation, covering *triage*, *mortality prediction*, and *sepsis monitoring*—domains where explainable outputs are critical for time-sensitive, high-stakes decision-making [7, 8, 32].

The third cluster focuses on ethical and human-centered dimensions, emphasizing recurring themes of *bias*, *accountability*, *transparency*, and *trust*, which mirror the field's growing concern with responsible and equitable AI adoption [22, 33, 34].

Finally, the emerging topics cluster underscores the growing integration of *large language models (LLMs)* and *generative AI* into emergency care, particularly in *pediatric* and *geriatric* populations, signaling a new phase of explainability research centered on demographic and contextual adaptability [23, 35].

The Sankey diagram (Fig. 6) visualizes the thematic interconnections among these clusters and their leading contributors. Influential researchers, such as Ong M.E.H., Dwivedi G., and Song J., serve as intellectual bridges linking methodological development, ethical discourse, and clinical implementation. Their cross-domain contributions illustrate how, although scholarly leadership remains concentrated within a small core group, the field is becoming increasingly multidisciplinary, ethically grounded, and clinically embedded in its evolution.

Clinical applications in emergency medicine

Triage has been the most extensively investigated domain. Interpretable models consistently demonstrate superior performance in predicting hospital admissions, critical illnesses, and resource utilization compared to conventional tools. Explainability techniques such as SHAP and LIME have further enhanced clinician confidence by providing transparent reasoning, thereby addressing a key barrier to AI adoption in acute care settings [7, 8, 32, 36]. Similar results have been reported in broader emergency medicine reviews, where interpretable models not only improved predictive accuracy but also increased trustworthiness in high-stakes triage

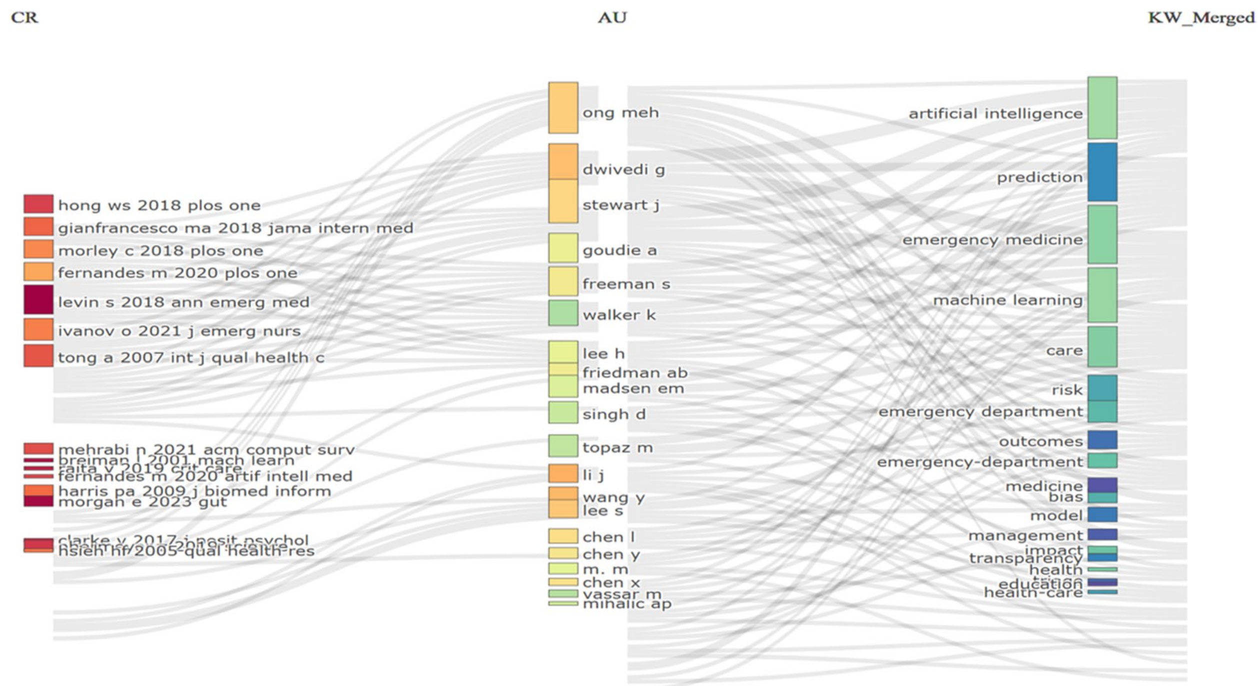

Fig. 6 Sankey diagram mapping the relationships between keywords, thematic domains, and leading authors in explainable artificial intelligence (XAI) research within emergency medicine.

decisions [17, 27]. Evidence from prehospital studies also supports this trend, showing that AI can predict the need for critical care in EMS settings [4].

Diagnostic imaging represents another critical application of XAI. These methods have the potential to reduce diagnostic delays in overcrowded emergency departments by enabling rapid prioritization of clinically significant findings [9, 10, 37]. Techniques such as saliency mapping and attention-based modeling have been particularly valuable in radiology, enhancing clinical plausibility and mitigating "black-box" concerns that often limit the integration of deep learning tools [20, 38]. Recent evidence further supports this potential: an AI system analyzing chest radiographs in ED patients with acute cardiopulmonary symptoms achieved higher accuracy in predicting major adverse events than conventional triage scores. An additional benefit was observed when AI predictions were combined with traditional approaches [39].

Mortality prediction and sepsis early warning systems have likewise benefited from interpretable machine learning. Transparent models outperformed traditional risk scores and provided feature-level explanations that support shared decision-making and facilitate communication with patients' families in ethically sensitive situations, such as end-of-life care [22, 40, 41]. Systematic evaluations further indicate that interpretable models are more easily integrated into existing decision-support frameworks, reinforcing their practical value in emergency workflows [16, 18]. Notably, the MARS-ED randomized pilot trial demonstrated the feasibility of implementing machine learning–based mortality prediction tools in real-world emergency department settings [42].

More recently, large language models (LLMs) such as ChatGPT and Gemini have been piloted for non-critical applications, including triage documentation, patient communication, and decision augmentation. Early reports suggest potential efficiency gains but also highlight risks related to variable accuracy and hallucination [23–25, 35]. Concerns are amplified by evaluations showing that AI chatbots, including ChatGPT, provided inconsistent adherence to resuscitation guidelines, exposing persistent reliability gaps [26]. Pilot studies, therefore, emphasize that successful integration of LLMs must prioritize contextual adaptation, safety, and active physician oversight to prevent overreliance and ensure clinical accountability [31, 34].

Ethical and social dimensions

The integration of explainable artificial intelligence (XAI) into emergency medicine raises ethical and social challenges that extend well beyond technical considerations. These include privacy, autonomy, fairness, accountability, transparency, and professional identity. Privacy and data security are particularly vulnerable as emergency workflows increasingly rely on large-scale electronic health records and interinstitutional data exchange, heightening the risk of breaches and patient re-identification [33, 43]. Unresolved questions of data ownership and the secondary use of information without explicit consent further complicate this landscape [34].

Safeguarding patient autonomy is especially difficult in time-critical emergency department settings, where traditional consent models are often impractical. Alternative approaches, such as proxy or dynamic consent, have been suggested to reconcile the urgency of acute care with patients' rights [22, 41]. Equally pressing are concerns regarding bias and fairness, since algorithms trained on historical datasets risk perpetuating inequities that disproportionately affect minority groups and older adults [22, 31, 34]. Addressing these disparities will require both technical strategies, such as debiasing methods, and policy measures, including transparent reporting standards [2, 36].

When comparing research orientations, XAI-focused studies primarily addressed algorithmic transparency, interpretability, and clinical usability, whereas ethics-centered investigations concentrated on governance, accountability, and fairness frameworks [2, 22, 44]. Overlapping studies—comprising nearly one-fifth of all publications—bridged these domains by integrating ethical reasoning into model development and validation workflows, emphasizing transparency and stakeholder engagement as essential design principles [33, 34]. This convergence demonstrates a conceptual maturation of the field, where explainability is no longer viewed merely as a technical feature but as a core principle of responsible AI deployment in emergency medicine [20, 36].

From a temporal perspective, the literature's thematic evolution reveals three distinct phases. Between 2018 and 2020, publications primarily focused on developing foundational explainability methods such as SHAP, LIME, and attention mechanisms for risk prediction and triage [3, 8]. From 2021 to 2023, the emphasis shifted toward bias mitigation, model calibration, and human-in-the-loop frameworks that prioritized interpretability, safety, and clinician trust [2, 17]. During 2024–2025, the field entered an expansion phase driven by the rise of large language models (LLMs) and generative AI systems for triage documentation, clinical summarization, and patient communication [30, 31, 45]. This progression reflects both methodological diversification and the growing ethical complexity of integrating autonomous decision-support tools into emergency workflows.

To ensure safe clinical translation, a structured governance checklist is proposed for XAI deployment in emergency departments, comprising seven interdependent domains: (1) governance and regulatory oversight; (2) bias detection and fairness auditing; (3) human-in-the-loop validation; (4) real-time monitoring and rollback mechanisms; (5) transparent documentation and model traceability; (6) clinician education and continuous competency training; and (7) incident reporting and accountability review [34].

Collectively, these elements ensure that explainability translates into operational safety, reproducibility, and trustworthiness, particularly in high-stakes decision-making.

At a broader system level, efficiency-driven algorithms may inadvertently compromise distributive justice, particularly for underserved populations, and risk diminishing public trust if AI-supported decisions are perceived as opaque or inequitable [22, 27, 34]. Given that this analysis relied exclusively on the Web of Science (WoS) Core Collection, engineering-oriented and regional contributions indexed in Scopus or IEEE Xplore may be underrepresented [7, 16]. Therefore, the findings should be interpreted as conservative estimates of the global XAI landscape in emergency medicine, emphasizing the need for multi-database validation in future bibliometric work.

Uncertainty also persists regarding accountability and liability for adverse outcomes arising from AI-supported decisions. Questions remain over whether responsibility lies with clinicians, healthcare institutions, or developers, underscoring the need for shared accountability frameworks supported by legal and institutional reforms [20, 38, 44]. At the clinical level, transparency and interpretability are increasingly important for trust. Explanations must be concise and context-relevant. Models that embed interpretability into workflow design have demonstrated greater clinician acceptance compared with post hoc explanatory methods [2, 3, 46].

Prehospital innovations further illustrate these challenges. For example, automatic speech recognition for stroke detection in EMS dispatch has demonstrated both potential and ethical implications, particularly regarding accountability and reliability [47]. Similarly, trauma-focused analyses use machine learning to predict the need for non-invasive ventilation before prehospital emergency anesthesia underscore the ethical complexities of deploying AI in high-stakes, time-critical scenarios [48].

Finally, physician autonomy and professional identity may be threatened by excessive reliance on AI, leading to a shift in clinical roles toward passive oversight. Recent surveys underscore these concerns, showing that while emergency physicians recognize AI's potential to improve patient care, they also express apprehension regarding bias, accountability, and the erosion of professional identity [49]. Ongoing training in AI literacy is therefore crucial for maintaining active clinical decision-making and preserving professional judgment [9, 19, 25]. At a broader system level, efficiency-driven algorithms may inadvertently compromise distributive justice, particularly for underserved populations, and risk diminishing public trust if AI-supported decisions are perceived as opaque or inequitable [27, 34]. Collectively, these concerns highlight that technical performance alone cannot justify adoption. Robust governance frameworks that incorporate the perspectives of clinicians, ethicists, policymakers, and patients are essential to ensure that XAI in emergency medicine aligns with principles of fairness, accountability, and transparency.

Future directions

Despite rapid progress, the application of explainable artificial intelligence (XAI) in emergency medicine remains in its early stages, and several steps are necessary to transition from proof of concept to routine clinical adoption. One of the most pressing priorities is prospective, multicenter validation, as most current studies rely on retrospective or single-center datasets that limit generalizability across diverse emergency populations [7, 8, 27]. Encouragingly, early initiatives such as the MARS-ED randomized pilot trial have demonstrated the feasibility of implementing machine learning–based mortality prediction models in real-world emergency department workflows [42].

A second critical priority is the standardization of interpretability metrics. Although methods such as SHAP and LIME provide valuable insights, they lack clinical consistency. This underscores the need for benchmarks capable of delivering concise, rapid, and actionable explanations tailored to emergency contexts [1, 50]. Ethical frameworks also remain underdeveloped. Because emergency encounters rarely allow comprehensive consent discussions, innovative approaches such as dynamic or proxy consent—embedded within governance structures that clarify accountability and liability—will be essential [22, 41].

Technical innovation must progress in parallel. Federated learning and privacy-preserving architectures are particularly promising, as they enable cross-institutional collaboration while protecting confidentiality and ensuring dataset diversity [43, 51]. At the same time, the rapid emergence of large language models (LLMs) such as ChatGPT and Gemini demands systematic evaluation. While they show promise in documentation and triage support, concerns about hallucination and inconsistent accuracy highlight the need for rigorous validation and robust explainability standards before clinical integration [23, 30]. Recent evaluations of chatbot adherence to resuscitation guidelines further emphasize these risks, revealing significant reliability gaps and reinforcing the importance of explainability in safety–critical scenarios [26].

Ultimately, the long-term success of XAI in emergency medicine will depend on sustained multidisciplinary collaboration. Clinicians, data scientists, ethicists, and policymakers must work together to balance innovation with accountability, supported by regulatory oversight and ongoing physician training in AI literacy [34, 38, 52]. Addressing these challenges will allow the next phase of XAI research to move beyond algorithmic development toward establishing a trusted, transparent, and equitable role for AI in emergency care.

Strengths and limitations of the study

A key strength of this study lies in its transparent and systematic methodology. The exclusive use of the Web of Science (WoS) Core Collection ensured a rigorously indexed dataset with structured metadata and a comprehensive citation network, thereby supporting reproducibility and comparability with previous bibliometric research in healthcare and artificial intelligence. The application of established tools such as Bibliometrix (R) and VOSviewer further enhanced the robustness of the analyses by enabling multifaceted evaluations of publication trends, thematic structures, and author networks.

Several limitations should also be acknowledged. The reliance on a single database may have excluded relevant records indexed in Scopus, PubMed, or IEEE Xplore, particularly those originating from engineering domains or conference proceedings. Similarly, the restriction to English-language publications may have overlooked contributions from non-English-speaking regions, potentially underrepresenting global perspectives. While these limitations do not compromise the validity of the findings, they suggest that future research could benefit from integrating WoS with complementary databases to capture a broader and more diverse body of literature. Additional limitations include potential query sensitivity in Topic searches (e.g., varying use of terms such as interpretability, transparency, and explainability), the exclusion of conference proceedings that may be influential in computer science, and the inherent time lag in citation accrual, which disadvantages recent publications. Finally, any trend forecasting based on growth models should be interpreted cautiously because publication dynamics can change rapidly in response to policy, funding, and shifts in clinical adoption.

Conclusion

Explainable artificial intelligence (XAI) is becoming an increasingly important component of emergency medicine, with research activity accelerating markedly since 2018. This bibliometric analysis indicates that scholarly output is concentrated in a small number of high-impact journals and is shaped by a limited but influential group of authors, spanning methodological, clinical, and ethical dimensions.

Despite this momentum, the field remains in its early stages, dominated by retrospective studies and conceptual models. Notable gaps include the absence of prospective, multicenter validation, the lack of standardized interpretability metrics, and underdeveloped ethical frameworks tailored to acute care. Emerging approaches—such as large language models and federated learning—offer considerable promise but require rigorous validation, clear standards for explainability, and robust governance structures before being integrated into clinical workflows.

Future progress will depend on sustained multidisciplinary collaboration that balances innovation with accountability. Clinicians, data scientists, ethicists, and policymakers must work together to ensure that transparency, fairness, and patient autonomy remain central. Addressing these challenges will be critical to transforming XAI from a promising concept into a trusted, transparent, and equitable tool in emergency care.

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Authors' contributions
Conceptualization, Methodology, Formal analysis and investigation, Writing – original draft preparation, Writing – review and editing, Resources, and Supervision: Meliha Fındık. For this review article, the study concept was conceived by Meliha Fındık, who also performed the literature search, bibliometric data analysis, drafting, and critical revision of the manuscript.

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Data availability
All data analyzed in this study were retrieved from the Web of Science Core Collection. The dataset is publicly available and can be accessed using the search strategy described in the Methods section.

Declarations

Ethics approval and consent to participate
Not applicable. This study relied solely on bibliographic data and did not involve human participants, animals, or tissue samples.

Competing interests
The authors declare no competing interests.

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