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RESEARCH

Artificial intelligence in hematology: current trends and application areas

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Abstract

This study aims to map the current research trends, application areas, and thematic clusters of artificial intelligence (AI) technologies in hematology. A literature search was conducted in the Web of Science on June 1, 2025, covering the years 1980–2025. A total of 376 original research articles were analyzed using bibliometric techniques, including trend keyword and factor analyses, via the bibliometrix package in R Studio. The USA ($n = 111$), China (79), the United Kingdom (22), and Germany (21) were the most productive countries, with Harvard University as the leading institution. Keywords revealed research concentration in thrombosis, venous thromboembolism, risk assessment, hematopoietic stem cell transplantation, atrial fibrillation, anticoagulants, morphological analysis, blood management, sepsis, and acute myeloid leukemia. Recent years have shown rising interest in transcriptome, prediction modeling, hematopoietic stem cell transplantation, blood management, thrombosis, venous thromboembolism cancer and COVID-19 related complications. Factor analysis grouped the literature into five clusters: AI and core hematologic diseases, clinical quality improvement, risk prediction using health data, intensive care, and cardiovascular applications. AI demonstrates substantial contributions to diagnostic accuracy, prognostication, and personalized care in hematology. The findings highlight AI's growing potential in enhancing clinical decision-making and improving patient outcomes through data-driven and genomics-based innovations.

Keywords Hematology · Artificial intelligence · Deep learning · Machine learning · Bibliometric analysis

Glossary of Abbreviations

AF	Atrial Fibrillation
aGvHD	Acute Graft-versus-Host Disease
AI	Artificial Intelligence
AML	Acute Myeloid Leukemia
AUC	Area Under the Curve
CML	Chronic Myeloid Leukemia
CNN	Convolutional Neural Network
DL	Deep Learning
DVT	Deep Vein Thrombosis
EFS	Event-Free Survival
EHR	Electronic Health Record
GVHD	Graft-versus-Host Disease
HSCT	Hematopoietic Stem Cell Transplantation
ICU	Intensive Care Unit
LLM	Large Language Model
ML	Machine Learning
NLP	Natural Language Processing
NOS	Not Otherwise Specified
RSF	Random Survival Forest
VTE	Venous Thromboembolism

Introduction

Hematology is the branch of medicine concerned with blood and blood disorders, involving complex processes in diagnosis, treatment, and patient follow-up [1]. In recent years, with the widespread adoption of artificial intelligence (AI) technologies in medicine, their use in hematology has also rapidly increased [2, 3]. AI offers significant advantages in areas such as early diagnosis of hematologic diseases, treatment planning, prognosis prediction, and patient management [4, 5]. In particular, machine learning (ML) and deep

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learning (DL) algorithms strengthen clinical decision support systems by analyzing large datasets, enabling physicians to make more accurate diagnoses [6].

AI-assisted imaging techniques stand out in the diagnosis of hematologic diseases. For instance, automated analysis of peripheral blood smears provides great convenience in the early diagnosis of malignancies such as leukemia and lymphoma [7]. Similarly, digital pathology of bone marrow biopsies and AI-based classification models reduce the workload of pathologists in diagnosing myeloproliferative neoplasms [8]. Moreover, DL-based predictive systems have been developed to estimate post-treatment complications and support personalized therapeutic strategies [9]. In transfusion medicine, AI has also been effectively applied. Hurley and colleagues demonstrated that large language models such as GPT-4 perform with high accuracy in blood transfusion decision-making [10]. Likewise, Civettini et al. (2024) tested the potential of large language models in hematology-related clinical decision-making and indicated that, although still limited, these systems could serve as significant assistive tools [11].

All these developments demonstrate that AI has rapidly become a growing area of research and application in hematology. Bibliometric studies play an important role in highlighting emerging trends in rapidly developing fields such as AI and hematology and provide valuable insights that shape the direction of future research [12, 13]. Understanding the potential impact of AI technologies in hematology will serve as a guide for clinicians and researchers. The aim of this study is to evaluate the current trends, application areas, and research clusters of AI in the field of hematology through a bibliometric analysis. In this context, the study specifically seeks to answer the following key questions: What are the dominant AI techniques in hematology research after 2020? In which hematologic subfields are AI applications more intensely investigated? And with which clinical terms or diseases is AI most frequently associated?

Methods

Search strategy

A comprehensive literature search was conducted on June 1, 2025, using the Web of Science (WoS) Core Collection database (Clarivate Analytics, Philadelphia, PA, USA), covering studies published between 1980 and 2025. The WoSCC database was selected as the sole data source because it is widely regarded as the most suitable database for bibliometric analyses, offering rigorous coverage of high-impact journals, reliable citation indexing, and an extensive historical record of publications. WoSCC is frequently used in bibliometric studies across diverse fields, given its compatibility with advanced bibliometric software and its ability to support co-authorship, co-citation, and network analyses [14]. Although databases such as Scopus and PubMed provide complementary strengths, including broader interdisciplinary coverage and MeSH-based indexing, WoSCC remains the most widely adopted standard in bibliometric research and has been employed in recent high-quality studies [15].

The search was restricted to publications classified under the "Hematology" research area. To identify AI-related literature, keywords such as "artificial intelligence," "AI," "ChatGPT," "ML" "DL", "neural networks," and "large language model" were combined using Boolean operators (AND, OR). All details of the search strategy, including the keywords, Boolean operators, filters, and limitations used, were presented in detail in Supplementary File 1 to ensure the reproducibility of the study. The initial search yielded a total of 1,362 publications related to AI within the field of hematology. After excluding non-original research publications such as letters, proceedings, and review articles, 376 original research articles were included in the bibliometric analysis. A flowchart outlining the publication selection process is also provided in Supplementary File 1.

Statistical and bibliometric analysis

Basic statistical analyses were conducted using SPSS software (Version 25.0, SPSS Inc., Chicago, IL, USA). Microsoft Office Excel was used to visualize the distribution of publications over time. Bibliometric analyses were carried out using the Bibliometrix package via the Biblioshiny interface in RStudio (http://www.bibliometrix.org/) [16]. Bibliometrix is a widely used, robust, and comprehensive tool for analyzing bibliometric characteristics of scientific publications and visualizing literature networks. Due to its advanced analytical capabilities, it provides significant advantages over other software and is preferred more frequently in bibliometric evaluations [12, 13].

Results

Global productivity

All remaining findings related to global productivity, including data on countries, authors, institutions, and journals, are presented in Supplementary File 2. Notably, countries with five or more publications on AI in hematology (based on the affiliation of the corresponding authors) are presented in Fig. 1a. In addition, a bar chart showing the distribution of AI-related articles by year is provided in Fig. 1b.

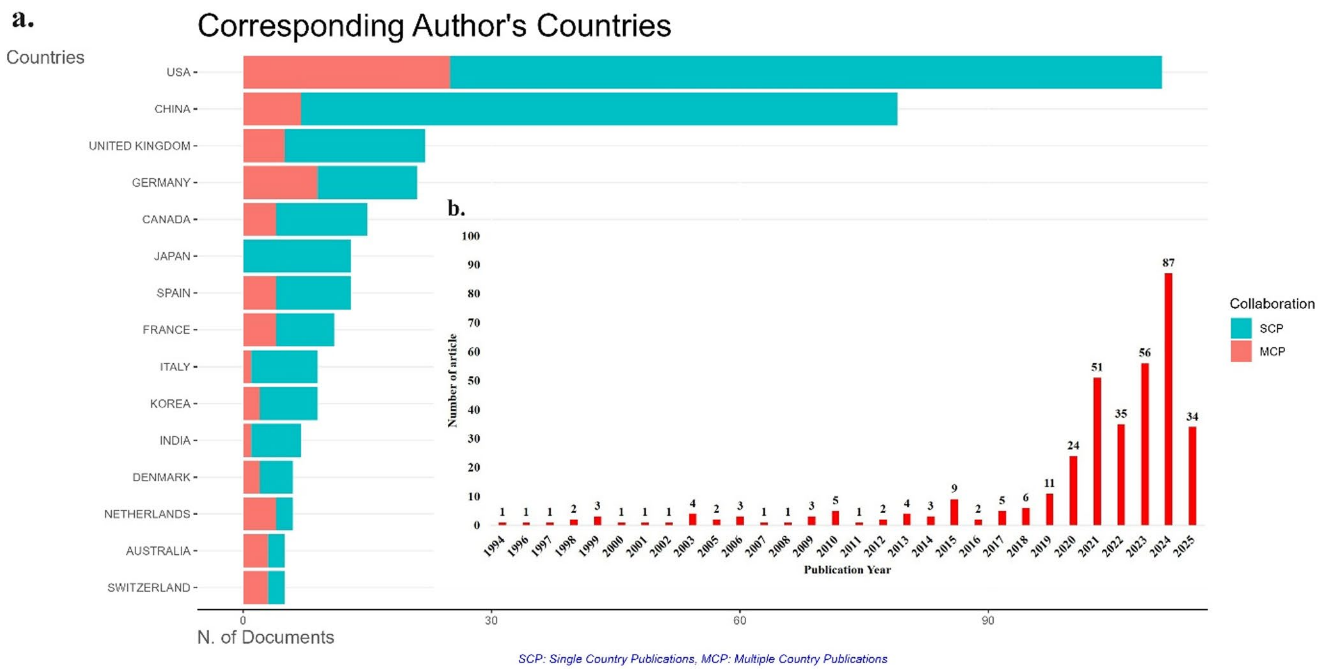

Fig. 1 **(A)** Countries that have published five or more articles on artificial intelligence in haematology. **(B)** Bar charts showing the distribution of articles on artificial intelligence in haematology by year

Trend topic analysis

A total of 957 different keywords were used across the 376 articles related to AI. Before conducting the analysis, synonymous terms such as “haemorrhage, hemorrhage”, “leukaemia, leukemia”, “magnetic resonance imaging, MRI”, and “diffuse large B-cell lymphoma, DLBCL” were consolidated, and the analyses were performed using the revised keyword pool. The top 50 author keywords that appeared in five or more articles are presented in Fig. 2a. In addition, to identify keywords specifically related to hematology, search terms such as “AI”, “neural network”, “ML”, “DL”, and “ChatGPT” were excluded from the analysis. Hematology-specific author keywords that appeared in five or more articles are shown in Fig. 2b. In the field of AI in hematology, the most frequently used keywords (in more than five articles) included: thrombosis, venous thromboembolism (VTE), risk assessment, pulmonary embolism, HSCT, atrial fibrillation, mortality, anticoagulants, morphological analysis, blood management, deep vein thrombosis, diagnosis, haemorrhage, prognosis, sepsis, acute myeloid leukemia (AML), electronic health records, hemodialysis, leukaemia, quality improvement, sickle cell disease, cancer, COVID-19, platelet count, prophylaxis, stroke, and transfusion medicine (Fig. 2b). A word cloud visualization showing the proportional frequency of the top 50 keywords is presented in Fig. 3.

To explore temporal changes, a trend analysis of author keywords was conducted, and the findings are presented in Fig. 4. According to the results of the trend keyword analysis, the evolution of AI research in hematology over time can be traced. In the early years, topics such as “statistics” and “warfarin” were prominent in 2009, while in 2016, “flow cytometry” emerged as an important diagnostic tool. In 2017, “cardiovascular disease” became a trending topic, followed by “acute leukemia”, “donor selection”, and “survival” in 2018, which reflected a focus on clinical and prognostic themes. By 2019, “atherosclerosis” and “VTE” came to the forefront, while in 2020, both disease-related and methodological topics such as “leukaemia/acute myeloid leukaemia”, “cerebral blood flow”, and “logistic regression” became trending. In 2021, the rise of AI techniques became more evident, with technical themes such as “diagnosis,” “morphological analysis”, “natural language processing (NLP)”, “artificial neural networks”, and “image analysis” drawing attention. In 2022, clinical and disease-specific topics including “atrial fibrillation”, “anticoagulants”, “electronic health records”, “hemodialysis”, and “sickle cell disease” were prominent. By 2023, subjects such as “pulmonary embolism”, “risk assessment”, “ML”, and “DL” were frequently studied, and

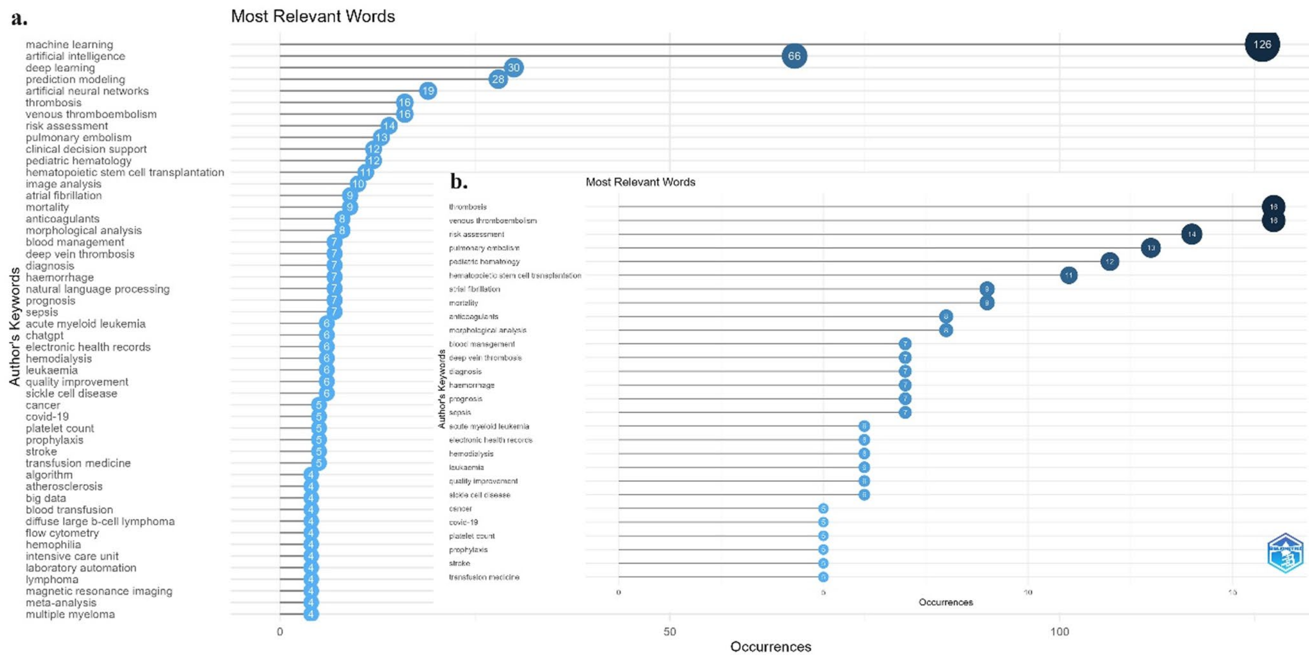

Fig. 2 **(A)** A graph showing the top 50 author keywords most frequently used by authors in articles on artificial intelligence in haematology. **(B)** Author keywords most frequently used in conjunction with artificial intelligence in articles directly related to the field of haematology

"HSCT" also emerged as a notable trending topic in this period. In 2024, there was a marked concentration on AI-driven applications, with trending topics including "AI", "prediction modeling", "thrombosis", "VTE", and "clinical decision support". The prominence of VTE and thrombosis in 2024 likely reflects interest in complications associated

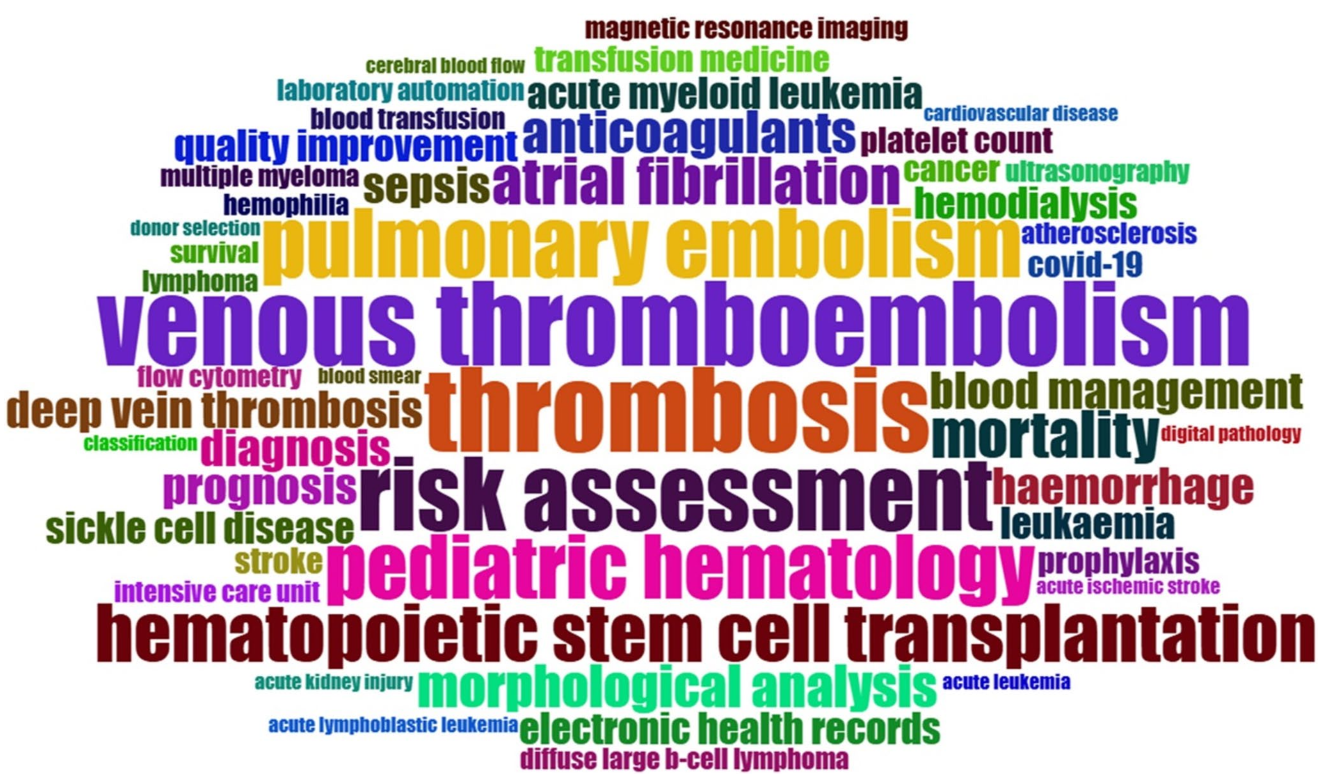

Fig. 3 A word cloud visualization showing the proportional density of the top 50 keywords most frequently used by authors in articles on artificial intelligence in the field of haematology

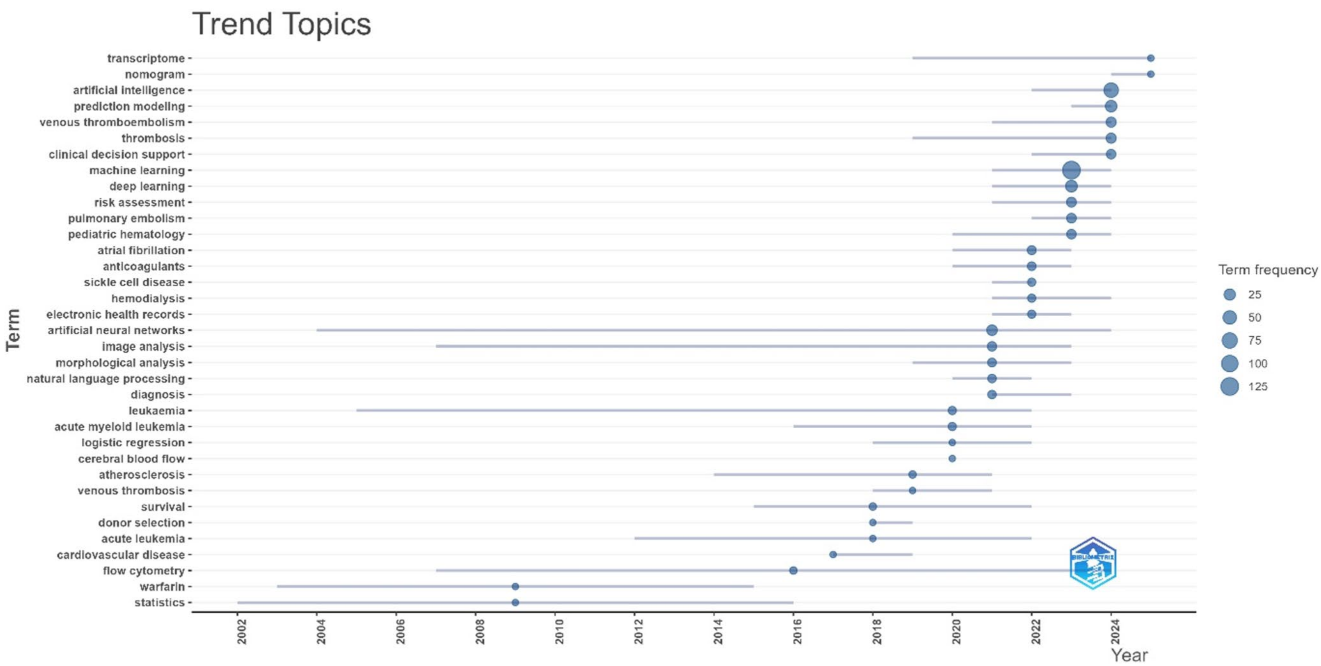

Fig. 4 A graph showing the trend analysis of author keywords in articles on artificial intelligence in the field of haematology from the past to the present. Footnote: Horizontal lines indicate the years in which keywords were used, while the size of the circles indicates the frequency of use

with the post-COVID-19 era. Finally, in 2025, there was increased interest in more advanced analytical techniques, such as “nomogram” and “transcriptome”. Additionally, to isolate trends specific to hematology, AI-related search terms were excluded, and the results of this focused trend analysis are presented in Fig. 5.

Factor analysis

The results of the factor analysis conducted using the 80 most influential keywords divided the AI literature in hematology into five main clusters (Fig. 6), contributing to a better understanding of the conceptual framework in this field.

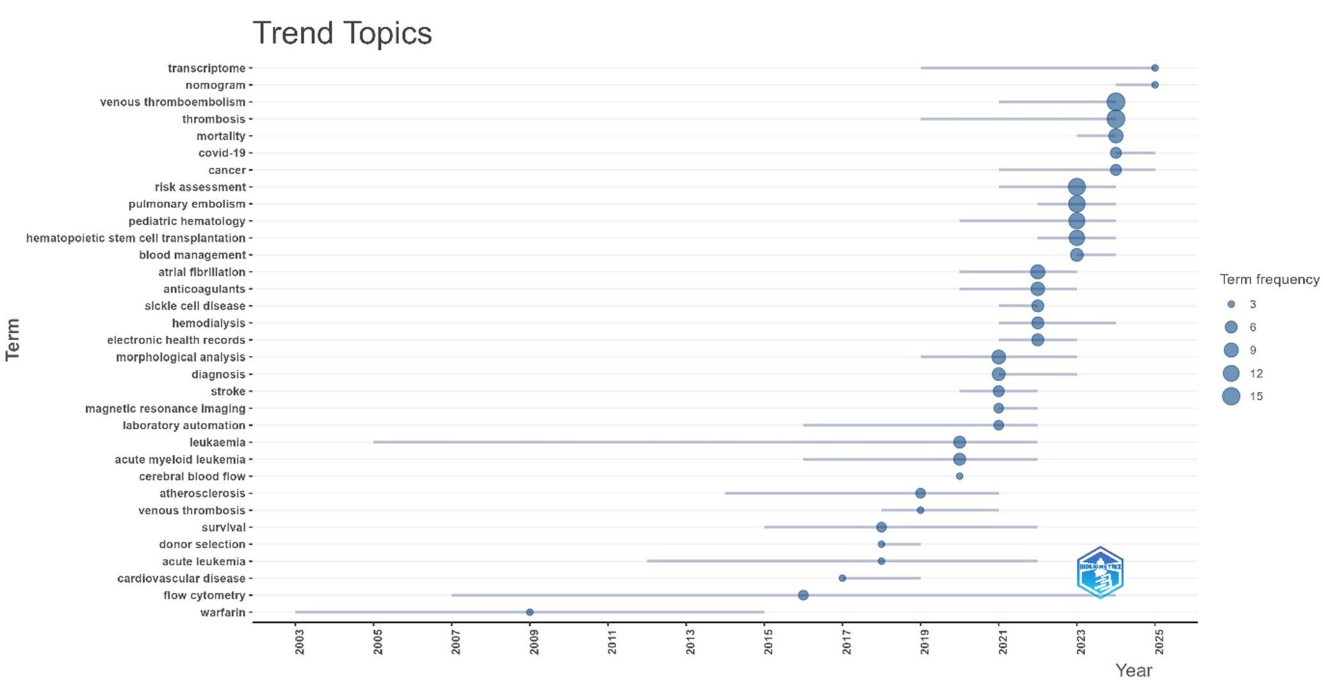

Fig. 5 After extracting keywords related to artificial intelligence, a graph showing the trend analysis of haematology topics from past to present. Footnote: Horizontal lines indicate the years in which keywords were used, while the size of the circles indicates the frequency of use

Fig. 6 Factor analysis visualisation performed using Multiple Correspondence Analysis with the 80 most effective keywords. Footnote: The centre of the map represents the main theme of the research topic and highlights the primary topics. Each colour represents a different sub-dimension

Detailed findings regarding the interpretation of the clusters, as well as all keywords included in the factor analysis and their associated clusters, are presented in Supplementary File 3.

Discussion

Temporal trends and growth of AI research in hematology

An examination of the temporal distribution of publications on AI in the field of hematology reveals a significant upward trend beginning in 2019, with an accelerated increase after 2020 and peaking in 2024. This surge, particularly between 2019 and 2024, clearly indicates the rapid integration of AI technologies into the diagnosis, treatment, monitoring, and decision-support processes for hematologic diseases, as well as the growing interest of researchers in exploring the potential of these technologies. Behind this increase lie advancements in ML and DL techniques, along with the rising availability of large data sources such as digital pathology, flow cytometry, and electronic health records. The digital transformation accelerated by the COVID-19 pandemic (2020–2021) also appears to have contributed significantly to this trend. It is foreseeable that this momentum will continue in the coming years, with AI applications becoming increasingly central to hematology practice.

Clinical applications of AI in thrombosis and VTE

Thrombosis and VTE have been the most intensively studied areas where AI has demonstrated clinical utility. Gil et al. (2023) comprehensively demonstrated how AI algorithms are utilized across a wide spectrum—from screening for VTE to managing its treatment—and emphasized the revolutionary potential of large language models and generative AI techniques in healthcare data processing [17]. Similarly, Ding et al. (2023) developed an XGBoost model to predict the development of DVT and pulmonary embolism following hip arthroplasty, reporting 91.3% sensitivity and 99.8% specificity, thereby surpassing conventional scoring systems in predictive performance [5]. Wang et al. (2023) reported high accuracy with an AI model developed for estimating the risk of DVT after hip and knee arthroplasty, achieving an AUC of 92% and a sensitivity of 80.3%

[4]. Ryan et al. (2024) highlighted the potential of AI models to reduce mortality by predicting deep vein thrombosis 12–24 h in advance [18]. The effective use of electronic health records in these models provided stronger predictive capabilities compared to traditional scoring systems such as Caprini, improving both diagnostic accuracy and prognosis assessment in clinical practice. These AI-assisted early warning systems offer clinicians critical advantages in the early detection of complications and timely intervention in patient management.

AI in HSCT

HSCT represents another domain where AI has shown clear added value. Pagliuca et al. (2024) employed Random Survival Forest (RSF) and Lasso/Elastic Net models to investigate the impact of various immunogenetic variables—particularly HLA Evolutionary Divergence (HED)—on outcomes following allogeneic stem cell transplantation. Their findings revealed that HED values were predictive of critical outcomes such as relapse, acute and chronic graft-versus-host disease (GVHD), and overall survival [19]. Importantly, this study used a multi-center dataset, which enhances generalizability. The MatchGraft. AI model, based on a random forest algorithm, successfully predicted individual aGvHD risk in an international retrospective cohort of 1,035 patients, demonstrating its clinical decision support potential with an AUC performance of 70% [20]. This model enables a broader and more precise donor selection process and facilitates the development of individualized conditioning and treatment plans [20]. While the predictive power is modest, the model illustrates how AI can complement existing donor-selection strategies. In addition, a CNN (convolutional neural network) based model developed using the Japanese national registry database integrated NLP and interpretable AI algorithms to classify aGvHD risk among 18,763 patients. The model confirmed a 28.8% incidence of aGvHD in the high-risk group within the test cohort, significantly outperforming traditional methods in predictive accuracy [21]. Similarly, Spellman et al. (2024) went beyond traditional criteria used in unrelated donor selection and applied a “Nonparametric Failure Time Bayesian Additive Regression Trees” algorithm to more precisely assess the impact of donor age and sex on transplant outcomes [22]. Using a large dataset of over 11,000 patients, their analysis revealed that donors aged 18–30 showed comparable performance in overall survival, while male donors significantly improved event-free survival (EFS) [22]. Collectively, these studies show how AI can refine donor matching, stratify risks more precisely, and potentially improve individualized conditioning strategies—though prospective validation remains a gap.

AI-driven diagnostics and prognosis in leukemia

In acute myeloid leukemia (AML), AI applications have primarily focused on diagnosis from blood or marrow images and prognostic modeling. A meta-analysis by Al-Obeidat et al. (2025) demonstrated that DL algorithms such as CNNs can detect AML cases from microscopic blood images with high accuracy (over 95%) and sensitivity [23]. Similarly, Achir et al. (2024), in a systematic review encompassing over 25,000 studies, emphasized that AI and image processing techniques not only enhance diagnostic accuracy but also improve speed and reliability, particularly in low-resource healthcare settings [24]. For genetically undefined or clinically heterogeneous subtypes such as AML not otherwise specified (AML-NOS), AI-supported models also offer promising prognostic capabilities. A RSF algorithm developed by López-Caro et al. (2024) and tested on data from 286 patients was able to stratify AML-NOS cases into low-, intermediate-, and high-risk groups with a concordance index (c-index) exceeding 0.77 in both clinical-only and genomics-integrated models [25]. Despite these promising outcomes, most models are limited by small sample sizes or retrospective validation, underlining the need for prospective clinical trials.

By contrast, in chronic myeloid leukemia (CML), the clinical impact of AI remains limited. Bernardi et al. (2024) showed that AI contributes to diagnosis and monitoring, including virtual patient cohort generation and big data analytics [26]. However, given the high success of current treatment regimens, AI’s role is still exploratory and lacks direct clinical translation.

Broader clinical integration across hematologic disorders

Beyond VTE, HSCT, and leukemia, AI has also been increasingly applied to other clinically relevant conditions in hematology. These include atrial fibrillation, anticoagulation therapy, morphological analysis, sepsis, and sickle cell disease. Zhao et al. (2023) developed a ML model to predict left atrial appendage thrombosis in atrial fibrillation patients, demonstrating the feasibility of personalized risk assessment [27]. Fard et al. (2024) showed that AI-based models predicting bleeding risk during extended anticoagulation therapy outperformed conventional methods [28], while Chrysafi et al. (2024) extended the role of AI into pharmacological innovation by supporting the design of novel anticoagulant molecules [29]. In high-mortality hematologic disorders such as sickle cell disease, AI has also shaped patient management: Patel et al. (2024) predicted hospital readmissions more accurately than traditional scores such as LACE and HOSPITAL [30], and

Padrao et al. (2021) successfully stratified mortality risks in intensive care using phenotype-based clustering [31]. Taken together, these studies illustrate that AI contributes not only to diagnosis and prognosis but also to drug development and personalized care, underscoring its broadening scope across diverse hematologic conditions (Fig. 2a).

Thematic evolution and emerging research frontiers (2021–2025)

According to the findings of the trend analysis, research in the field of hematology initially focused on basic statistical methods (e.g., survival analysis, logistic regression) and classical hematologic diseases. However, in recent years, the integration of advanced AI techniques has led to a more multidimensional research landscape. Notably, after 2021, topics such as "ML", "DL", "NLP", and "clinical decision support" have gained prominence, indicating a widespread adoption of AI in both clinical decision-making and image/text analysis. In terms of clinical integration, AI applications have expanded from diagnostic processes to include decision support and risk assessment. Temporally, the early focus on anticoagulation (e.g., warfarin) has evolved toward AI-supported thrombosis management (e.g., VTE and pulmonary embolism). The emergence of topics like "nomogram" and "transcriptome" in 2024 and 2025, respectively, suggests a shift toward personalized medicine and genomics-based approaches. Overall, these findings indicate not only thematic diversification but also a gradual move from retrospective, statistical analyses toward prospective, genomics-driven approaches.

In 2021, the prominent AI-related trends in hematology were "diagnosis" and "stroke." Matek et al. (2021) demonstrated the potential of DL techniques for the accurate classification of bone marrow cell morphology [32]. Benzakoun et al. (2021) employed ML techniques in the context of ischemic stroke to model tissue outcomes associated with thrombosis and anticoagulation-related factors, reflecting the cross-disciplinary applications of AI across hematology and vascular medicine [33]. These studies underscore AI's growing role in enhancing diagnostic accuracy and prognosis planning in hematology. In 2022, major themes included atrial fibrillation, anticoagulants, hemodialysis, and sickle cell disease. A study aimed at predicting cerebral infarction risk in atrial fibrillation patients showed that ML models improved risk assessment [34]. Similarly, AI-based models were used to predict adherence to anticoagulant therapy, thereby supporting stroke prevention strategies [35]. For patients undergoing hemodialysis, ML methods provided improved bleeding risk evaluations compared to traditional scoring systems [36]. However, most of these studies relied on retrospective datasets and lacked external validation, which may limit immediate clinical translation. Collectively, they nonetheless illustrate AI's potential in risk classification and therapeutic decision support.

In 2023, the highlighted research topics were risk assessment, pulmonary embolism, and HSCT. In 2024, attention shifted to thrombosis, VTE, mortality, cancer, and COVID-19. Clinical decision support systems were employed in the diagnosis of heparin-induced thrombocytopenia, aiming to reduce diagnostic delays and associated mortality [37]. AI-based modules were also utilized to analyze COVID-19–related thrombotic complications, particularly in pediatric patients, to improve VTE prophylaxis [38]. Furthermore, AI models were compared in predicting thrombosis risk among COVID-19 patients, with ensemble learning strategies emerging as particularly effective [39]. In oncology, the automation of RH genotyping via AI contributed to the optimization of transfusion strategies in patients with sickle cell disease [40]. Together, these studies highlight how AI is being extended into complex infectious and neoplastic contexts, although many remain proof-of-concept and require prospective validation. In 2025, research trends shifted toward the use of nomograms and transcriptomic approaches. In a significant study, a nomogram combining clinical and biochemical data was developed to predict 30-day mortality in patients with hemophagocytic lymphohistiocytosis [41]. Lin et al. (2025) utilized a Bayesian network meta-analysis to analyze VTE events associated with immune checkpoint inhibitors, demonstrating an innovative application of AI in the field of pharmacovigilance [42]. Collectively, these studies reflect a progressive integration of AI into predictive, pharmacovigilance, and genomic domains within hematology, while also underscoring the current gap in prospective clinical applications.

Conceptual clustering and research domains identified by factor analysis

The factor analysis conducted in this study conceptually classified AI research in hematology, revealing current trends across five main thematic clusters. The first cluster associated advanced technologies, such as AI, ML, and DL with core hematologic topics like leukemia, sickle cell disease, HSCT, and blood transfusion, thereby demonstrating the strong integration of AI into diagnostic, prognostic, and therapeutic processes. The second cluster focused on quality improvement and epidemiological applications, highlighting AI's contributions to clinical decision support systems and outcome monitoring in healthcare. The third cluster emphasized data-driven approaches such as NLP and electronic health records, underscoring the development of risk prediction models and personalized treatment strategies.

The fourth cluster shed light on the application of AI in intensive care and critical patient management, while the fifth cluster reflected the importance of AI-based solutions in addressing the interactions between hematologic diseases and the cardiovascular system.

This clustering structure demonstrates that AI provides tailored solutions to diverse clinical needs in hematology and systematically reveals its multidimensional contributions, offering important insights for both researchers and clinicians regarding interdisciplinary collaborations and new research frontiers. Particularly, the technology-disease interaction identified in the first cluster highlights the integration of technology-centered approaches with healthcare service quality, enhancing diagnostic accuracy and optimizing treatment protocols. Additionally, the integration of NLP techniques with electronic health records (third cluster) enables the development of clinical decision support systems through the automated analysis of patient data. Similarly, the clusters focused on intensive care and cardiovascular conditions support the use of AI for prognostic modeling and early warning systems in complex clinical scenarios.

Limitations of the study

Although the findings of this study provide valuable contributions to the literature, they should be interpreted within the context of certain limitations. First, the bibliometric data were obtained exclusively from the Web of Science (WoS) Core Collection (WoSCC) database. As a result, potentially relevant studies indexed in other major databases such as Scopus or PubMed may have been excluded from the analysis. Compared with PubMed, WoSCC is less comprehensive in covering biomedical and clinical research, while PubMed's MeSH vocabulary allows for highly precise retrieval of biomedical studies, including clinical trials, which may not always be captured in WoSCC. In contrast, Scopus provides broader interdisciplinary and regional coverage and more frequently updated citation data, whereas WoSCC offers a longer historical record of citations. Consequently, the sole reliance on WoSCC may have led to the omission of certain medical intervention studies captured in PubMed or interdisciplinary/psychological studies indexed in Scopus [14, 15].

Nevertheless, WoSCC is widely recognized for its rigorous indexing of high-impact journals, robust citation tracking, and long-term archival coverage, making it one of the most reliable sources for bibliometric studies (14,15,43). Indeed, previous bibliometric analyses across diverse medical specialties have also employed WoSCC as the primary database given its suitability for co-citation, co-authorship, and network analyses [14, 15, 43]. Therefore, while this limitation may affect the absolute comprehensiveness of our findings, we are confident that the results largely reflect the mainstream and most influential body of literature in the field of AI in hematology.

Second, since this study has a cross-sectional design, the analyses are based on data available as of June 1, 2025. Newly published articles or updates to existing publications in the database may alter the findings over time. Nonetheless, this characteristic is inherent to bibliometric analyses, which aim to provide a snapshot of the literature within a specific time frame, and it does not compromise the methodological validity of the study [12, 40].

Conclusion

This bibliometric analysis demonstrates that AI technologies are rapidly evolving in the field of hematology, with a marked increase in research volume particularly after 2019. Initially limited to statistical analyses, AI applications have since diversified to include advanced techniques such as DL, NLP, and clinical decision support systems, which indicates their increasingly active role in clinical decision-making processes. Notably, AI has shown clinical utility in complex scenarios such as thrombosis, VTE, AML, HSCT, and risk assessment. The five key research clusters identified through factor analysis reveal AI's multifaceted contributions in hematology, ranging from diagnosis and epidemiological monitoring to personalized risk prediction, critical care management, and the anticipation of cardiovascular complications. Emerging topics such as nomograms and transcriptomics in recent years further suggest a shift toward genomics and personalized medicine. This study provides a comprehensive analysis of the current state of AI in hematology and underscores its transformative potential to enhance patient care quality, optimize clinical workflows, and open new avenues for future research.

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Data availability Data can be obtained by contacting the corresponding author. Data can be obtained by contacting the corresponding author.

Declarations

Ethics statement This article does not contain any studies with human participants or animals performed by any of the authors.

Competing interests The authors declare no competing interests.

Conflict of interest Authors declare that they have no conflict of interest.

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