Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 12 April 2026
Revised 18 May 2026
Accepted 16 June 2026

Natural Resources for Human Health 2026, Vol. 6 (3s): 421–439

KEYWORDS:
Artificial Intelligence, Deep Vein Thrombosis, Venous Thromboembolism, Machine Learning, Bibliometric Analysis, Deep Learning, Predictive Analytics.

Artificial Intelligence in Deep Vein Thrombosis: A Bibliometric Analysis of Diagnostic and Predictive Research

[1]Dr D. Jothieswari, M Pharm, [2]Dayala Ravi Kiran

[1]PhD, Professor, Sri Venkateswara College of Pharmacy, Chittoor-517127, drjothieswari@svcop.in, https://orcid.org/0000-0002-1352-0756- Corresponding author

[2]Research Scholar, Sri Venkateswara College of Pharmacy Chittoor (A), Research scholar JNTUA, darlingravi19@gmail.com, https://orcid.org/0009-0000-7177-9734

ABSTRACT:

Background: Artificial Intelligence (AI) use has been growing in Deep Vein Thrombosis (DVT) and Venous Thromboembolism (VTE) studies for diagnosis, risk prediction, prognosis and clinical decision-making. Although the field has seen rising trends over the past few years, a thorough bibliometric analysis of the research in the field of AI-powered DVT is still lacking.

Objectives: The aim of this study was to profile the global scientific landscape of the applications of AI in DVT and VTE by analysing the publication patterns, prominent contributors, collaboration networks, and research themes.

Methods: A bibliometric analysis was performed on the literature retrieved from PubMed with a search made up to 18/05/2026. The structured Boolean search incorporating artificial intelligence, DVT/VTE and clinical terms identified 561 publications. VOSviewer (v1.6.20) and Biblioshiny (Bibliometrix R package) were used to analyze data. The bibliometric indicators used were scientific production, citation performance, co-authorship and institutional collaboration, country productivity, keyword co-occurrence, thematic evolution and citation mapping.

Results: Scientific production also rising significantly in recent years, As a result of the increasingly wide incorporation of machine learning and computational science in the study of thrombosis. The United States and the United Kingdom were the top contributors, and the University of Maryland system came out as a significant hub of collaboration. Commonly used terms were “machine learning,” “deep vein thrombosis,” “venous thromboembolism,” and “artificial intelligence.” Key themes that developed included deep learning, natural language processing, imaging-based AI, and prediction of COVID-19-associated thrombosis. Citation analysis revealed basic research on VTE risk scoring and predictive modelling. **Conclusion**: while AI-powered DVT research is on the rise, there is a need for further prospective validation, explainable AI, and anticoagulation-focused applications.

1. INTRODUCTION

Deep vein thrombosis or DVT is a serious cardiovascular disorder that is the result of the formation of thrombi in the deep venous system, most commonly the lower limbs. It is associated with pulmonary embolism (PE) to form venous thromboembolism (VTE), causing around 900,000 cases and 60,000-100,000 deaths each year in the United States [1]. DVT is frequently underdiagnosed, with delayed diagnosis, high recurrence rates, and high cost of care, costing more than USD 10billion per year with hospitalization and long-term management. Diagnostic difficulties are exacerbated by unspecific symptoms and overlapping diseases, and the current assessment tools, such as the Wells score and D-dimer assays, are less efficient [2].

AI technologies, such as machine learning and natural language processing, have risen to the challenge of better diagnosing and treating DVT, and have surpassed traditional statistical models in several areas, including prediction of outcome and image analysis. From ultrasound diagnostics to predictive analytics using electronic health records, the applications of AI in DVT are varied. While much progress is made, the comprehensive understanding of the impact of AI in DVT research is not well developed yet [3].

Bibliometric analysis is an important tool for visualizing research trends and the intellectual landscape in a particular field of scientific research, providing information about the publication and citation patterns. Tools such as VOSviewer and CiteSpace enhance scientific metrics, revealing the growth and thematic evolution of AI in DVT research. While there have been several broad bibliometric studies conducted on AI use in healthcare, no detailed study has been done specifically on DVT.There is a huge research gap in the literature, as there is no extensive bibliometric study on the application of AI to the field of DVT. The systemic gap highlights the need for specific analysis to facilitate research collaboration, funding allocation and effective strategies in the dynamic field of AI and venous thromboembolism research [4].To fill this void, the authors of the present study have conducted the first in-depth bibliometric analysis of the published scientific literature on the topic of AI and DVT, systematically retrieved from Scopus and Web of Science (WoS) databases. The specific aims of this study are: (i) to characterize the global publication trend and the growth curve of AI-DVT studies over time, (ii) to identify countries, institutions, journals and authors that are most productive and influential in this field, (iii) to delineate international research networks for AI-DVT studies based on the co-authorship and bibliographic coupling analyses of publications, (iv) to map keywords and co-occurrence clusters to identify dominant research themes and emerging frontiers, (v) to assess the citation impact and identify seminal publications that have shaped the field, and (vi) to critically synthesize the findings to highlight current research gaps, the clinical implications of AI-DVT studies, and future directions. The goal of this research is to systematically address these objectives and give researchers, clinicians, funders and policy makers a scientometric basis for studying the intersection of vascular medicine and computational health sciences.

2. METHODS

2.1 Study Design

This study was planned in detail with regard to the reporting standards recommended for scientometric research set by APA PPAQ and BARS (Bibliometric Analysis Reporting Standards) guidelines. Primary data from human participants were not collected in the study and thus ethics committee approval was not required. The entire analytical pipeline from systematic retrieval of databases, to visualization of the retrieved networks and thematic mapping, was prespecified before data were extracted, in order to minimize analytical bias.

2.2 Search strategy and Data Sources

PubMed (MEDLINE), an online database published by the United States National Library of Medicine (NLM), was the most common bibliographic database chosen for literature retrieval. Selecting PubMed as the only retrieval source is justified because it contains a comprehensive coverage of biomedical and life science literature, the robust medical subject headings (MeSH) controlled vocabulary infrastructure and was relevant for clinically oriented bibliometric investigations. The last search was made on 18 May 2026 and the records were retrieved from all eligible records which were stored up to 18 May 2026.

A well-designed Boolean search strategy was developed a priori, consisting of three constructs with logical ANDs. The first block (Search #1) included all terms that referred to the domain of artificial intelligence selected by using an exhaustive MeSH and free text vocabulary (terms: Intelligence, Artificial or Artificial Intelligence [MeSH Terms] or Machine Intelligence or Computational Intelligence or Computer Reasoning or Computer Vision Systems or Knowledge Acquisition (Computer) or Knowledge Representation (Computer) combined by using the Boolean OR logic). 521,547 records were retrieved from this block. The second block (Search #2) retrieved 115,577 records – it exhaustively identified the clinical entity of deep vein and venous thrombosis with all the permutations of the terms in the nomenclature, using a controlled MeSH vocabulary and all

Boolean OR combinations. To see all the variants of a diagnosis/clinical focus, the third block entitled 'Search #3: clinical focus filter (wildcard truncation) was utilized for all Food Studies, which resulted in 14,062,080 records being found in the wider literature. When all three of the blocks were combined in the ultimate intersection (Search #4: #1 AND #2 AND #3), 561 records were present in the initial retrieval. The complete search history has been documented and presented in Table 1, which comprises both the search string, which represents the search term, and the search string MeSH expansion details and results from the translated search string.

Table 1. PubMed Search Strategy: Conceptual Blocks, Core Terms, and Retrieved Records (Search Date: 18 May 2026)

#	Concept	Core Search Terms (PubMed MeSH/All Fields)	Records Retrieved
1	Artificial Intelligence	Intelligence, Artificial; Computer Reasoning; Reasoning, Computer; AI (Artificial Intelligence); Machine Intelligence; Intelligence, Machine; Computational Intelligence; Computer Vision Systems; Knowledge Acquisition (Computer); Knowledge Representation (Computer) [MeSH Terms and All Fields combined with Boolean OR]	521,547
2	Deep Vein Thrombosis	Phlebothrombosis; Phlebothromboses; Thrombosis, Venous; Venous Thromboses; Deep Vein Thrombosis; Deep Venous Thrombosis; Deep-Vein Thrombosis; Deep-Venous Thrombosis; Thrombosis, Deep Vein [MeSH Terms and All Fields combined with Boolean OR]	115,577
3	Clinical Focus Terms	diagnos*; detect*; predict*; risk; screening; prognos* [All Fields, Boolean OR with wildcard truncation]	14,062,080
4	Final Combined Search (#1 AND #2 AND #3)	Boolean intersection of all three concept blocks (Search 1 AND Search 2 AND Search 3); no date or language restrictions applied at this stage	561

2.3 Eligibility Criteria

Inclusion and exclusion criteria were comprehensive and clearly defined before screening to prevent bias and to allow for systematic and reproducible studies to be identified. The selection of all criteria was uniformly done at the title/abstract screening and at the review of the full text. Details of the criteria are included in Table 2.

Table 2. Pre-specified Inclusion and Exclusion Criteria for Study Selection

Inclusion Criteria	Exclusion Criteria
Studies explicitly applying AI, ML, DL, or NLP methods to DVT	Studies not reporting primary AI or ML methodology applied to DVT
Studies addressing diagnosis, detection, prediction, risk assessment, screening, or prognosis of DVT/VTE	Duplicate records across database exports
Publications indexed in PubMed (MEDLINE) regardless of publication year	
Studies with retrievable full bibliometric metadata (authors, affiliations, keywords, citations)	Records with incomplete or unverifiable bibliometric metadata

Natural Resources for Human Health
eISSN: 2583-1194

The following bibliometric metadata for each retained publication were systematically extracted: publication title, author(s), author's affiliations, corresponding author country, journal name, publication year, volume, issue, page(s), DOI, abstract text, MeSH terms, author-submitted keywords, citations count, and funding information. Metadata were exported in the PubMed and comma separated value (CSV) file formats allowing downstream processing of the bibliometric software. Before analysis, each field extracted from the records in PubMed was cross-checked against the record's source data for data integrity.

2.5 Bibliometric Software and Analytical Tools

The VOSviewer software (version 1.6.20, Leiden University, The Netherlands) and Biblioshiny (web-based graphic interface of the Bibliometrix R package, version 4.x, R version 4.3+) were used for all bibliometric analyses, which were based on two mutually reinforcing applications. The purpose of using a dual platforms approach was deliberate as one for network building and the visualization of mapping was VOSviewer, while other qualitative performance indicators, productivity analyses and thematic evolution mapping was carried out using Biblioshiny. All the two platforms have been widely tested and validated in scientific bibliometric literature, being acknowledged as gold standard tools for scientometric research.

2.6 Bibliometric Indicators Analyzed

A versatile library of multidimensional bibliometric measures was examined to capture the multi-faceted nature of the knowledge base around AI-DVT research. These are presented in Table 3 and discussed in detail below.

Table 3. Bibliometric Indicators, Analytical Dimensions, and Corresponding Analytical Tools

Bibliometric Indicator	Analytical Dimension	Software/Tool
Annual publication output	Temporal growth and productivity trends	Biblioshiny (R Bibliometrix)
Citation count & h-index	Scientific impact and influence	Biblioshiny / VOSviewer
Co-authorship network	Author collaboration structure & link strength	VOSviewer
Institutional collaboration network	Organizational partnerships and productivity	VOSviewer
Country co-authorship & collaboration map	Geospatial distribution of research output	VOSviewer / Biblioshiny
Keyword co-occurrence (Author & MeSH)	Thematic clustering and research topics	VOSviewer
Thematic evolution (Sankey mapping)	Temporal shifts in dominant research themes	Biblioshiny
Document co-citation analysis	Intellectual base and citation clusters	VOSviewer
Bradford's Law / Lotka's Law	Core journal identification; author productivity	Biblioshiny

2.7 Statistical Considerations

Because of this, it was not possible to apply conventional null-hypothesis significance testing in this study, as this method is always descriptive and quantitative. Absolute values and percentages are provided to a suitable degree of accuracy for all counts, frequencies, proportions and network metrics. The network metrics (transitivity link strength, betweenness centrality and modularity) were algorithmically calculated in VOSviewer with well-established graph-theoretic methods. Growth rates were calculated on an annual basis as simple percentage changes and trend fitting by an exponential model was used if the data suggested the use of this model. No imputation of missing metadata was made, records that lacked affiliation or keyword data were kept for overall productivity analyses, but were not included in the analyses that required the missing field (e.g., country-level maps, keyword networks). The final cleaned data, after deduplication and eligibility screening, was analyzed.

Natural Resources for Human Health
eISSN: 2583-1194

RESULTS

Annual Publication Trends

In terms of scholarly production, the link between artificial intelligence (AI) and deep vein thrombosis (DVT) has been steadily building over the course of the study, with only a few initial publications appearing in the early years, followed by a surge of new research in the more recent years, driven by the integration of machine learning and computational techniques into venous thromboembolism (VTE) research (Figure 1A). This increase in the number of publications has been accompanied by an increase in citation numbers, reflecting the increasing use and development of this new research (Figure 1B). A cross-sectional distribution by domain shows that contributions were found across all of the streams of clinical research, computational research, and translational research, highlighting the inherently interdisciplinary nature of the field (Figure 1C). If focused on machine learning studies specifically relevant for VTE, research output has been increasingly concentrated in the last few years, representing a paradigm shift towards data-driven clinical decision-making in VTE medicine (Figure 1D).

Figure 1. Publication & Research Trend Analysis. The number of scientific publications related to artificial intelligence and deep vein thrombosis published in a year during study period (A) shows an increasing number of publications over time. Science's relationship to the field has grown over time, as is evident in the growth trend of the total publications and also the cumulative citation counts over time (B). (D) Distribution of publications by research domain and subject area, to show the scope of interdisciplinary contributions. (D) Temporal evolution of papers published on articles on venous thromboembolism and machine learning, with increasing use of AI methods over time.

Most Productive Authors

A total of 11 authors met the minimum requirement for their pool of publications to be included in the co-authorship analysis; each of these authors had at least five and at most six papers indexed. Lal, Brajesh K; Lam, Barbara D; Li, Ang; and Mayorga-Carlin, Minerva had the highest number of publications (6 each). Of these, Lal and Mayorga-Carlin showed the highest cumulative values of the co-authorship network weight metric (cumulative TLS) derived from VOSviewer that depicts the extent of recurring and substantive research collaboration. Hayssen, Phuong; Nguyen, Shalini; Sahoo, Shalini; Siddiqui, Tariq; and Yesha, Yelena each had five documents with the same TLS value of 34, indicating that they operate within a closely connected group, and possibly share similar institutional affiliations or grant programmes. Sorkin, John D made 5 documents that had a TLS of 30, a somewhat wider, but still significant level of network connectivity. Lam, Barbara D (TLS = 6), Li, Ang (TLS = 3), and Patell, Rushad (TLS = 3) on the other hand, showed a significantly lower level of network embeddedness despite similar or comparable output, which might indicate parallel but independent research programs (Table 1; Figure 2A).

Author	Documents	Total Link Strength
Hayssen, Hilary	5	34
Lal, Brajesh K	6	36
Lam, Barbara D	6	6
Li, Ang	6	3
Mayorga-Carlin, Minerva	6	36
Nguyen, Phuong	5	34
Patell, Rushad	5	3
Sahoo, Shalini	5	34
Siddiqui, Tariq	5	34
Sorkin, John D	5	30
Yesha, Yelena	5	34

Table 1. This is the top 10 most contributing authors in extensive Deep Vein Thrombosis research according to document count and also total link strength as measured by the number of links that point to the author from other research papers. Link strength values are summed-up to create "total link strength" values, which reflect co-authorship strength as calculated from the VOSviewer network analysis.

The most influential institutional/organizational collaboration networks North American academic medical centers' institutional productivity was dominated in AI-driven DVT research. The leading contributors in terms of the number of documents were the Department of Computer Science, University of Miami, with five documents (TLS = 7) and the Department of Medicine, University of Maryland School of Medicine, with five documents (TLS = 8), indicating ongoing computational and clinically oriented research programs. The University of Maryland system had the highest institutional concentration of activity in the field, as indicated by four additional documents from the Department of Surgery, also at the University of Maryland (TLS = 7). Three documents were contributed by the Department of Radiodiagnosis, Postgraduate Institute of Medical Education and Research, Chandigarh, India, and reported a TLS of 0, suggesting autonomous research activities and region specific research activities in the identified network. There were two documents coming from each of the European institutions (the United Kingdom [St. George's University of London, King's College London, Bristol Myers Squibb] and Spain [Hospital Universitario de Fuenlabrada, Hospital Universitario Infanta Leonor, Universidad Complutense de Madrid]); each such document has a TLS value of two, indicating the nascent but emerging bilateral cooperative ties. Activities of cross-continental type were clustered around the North American–European continents, while those of intra-European type were limited to the area being studied (Table 2; Figure 2B).

Organization	Documents	Total Link Strength
Bristol Myers Squibb Pharmaceutical Ltd, Uxbridge, UK	2	4
Cardiology Clinical Academic Group, Molecular & Clinical Sciences Research Institute, St. George's University of London, London, UK	2	4
Department of Computer Science, University of Miami, Miami, FL	5	7
Department of Haematological Medicine, Guy's and St Thomas' NHS Foundation Trust, King's College London, London, UK	2	4
Department of Internal Medicine, Hospital Universitario de Fuenlabrada, 28942 Madrid, Spain	2	4
Department of Internal Medicine, Hospital Universitario Infanta Leonor, 28031 Madrid, Spain	2	4
Department of Medicine, Universidad Complutense de Madrid, 28040 Madrid, Spain	2	4
Department of Medicine, University of Maryland School of Medicine, Baltimore, MD	5	8
Department of Radiodiagnosis, Postgraduate Institute of Medical Education and Research, Chandigarh, India	3	0
Department of Surgery, University of Maryland, Baltimore, MD	4	7

Table 2. The most productive institutions and organizational collaboration networks in the field of deep vein thrombosis research. Document counts show the number of papers that are indexed per institution, and total link strength shows the co-institutional network connectivity calculated by VOSviewer analysis. Thematic analysis Research into the global collaboration and country-wise scientific production The U.S. and also the UK contributed the bulk of AI-based DVT research, represented the largest index co-authorship world publications, and held the centrality roles in the world co-authorship network.

As for the Europeans, the geographical distribution of output was found to be similar to institutions, with Spain and the Western European axis showing a strong concentration. This first Indian representation, mainly through PGIMER, Chandigarh marks at least the beginning of South Asian scholarly activity in this field, although the inter-institutional cross-linkage was very light during the observation window. Partnerships largely took the form of bilateral links between North American and European institutions, with most areas of collaboration being between the United States and the United Kingdom. The lack of input from low- and middle-income countries other than India points to a longstanding geographical imbalance of AI-VTE research capacity across the globe (Figures 2C and 2D).

Figure 2. Author – institutional – country collaborations networks. Network visualizations of the co-authorship network of key researchers of deep venous thrombosis, where the nodes are sized according to the number of publications and the thickness of their edges according to the strength of the connection. I-INSTITUTIONAL COOPERATION NETWORK involving big

research institutes, showing inter-institutional connections. The map of countries worldwide (C) shows the scientific collaboration network in the field of venous thromboembolism research in colour intensity depending on the number of publications. (D) Visualisation of the international research partnerships and link strengths to visualise the bilateral corridors of collaboration. The identification of KeyWord Co-occurrence Networks and MeSH Term Analysis. The 'Humans' (475 occurrences, TLS = 1,929) and 'Male' (254, TLS = 1,500) and 'Female' (249, TLS = 1,481) MeSH descriptors were the most frequently used, showing the predominant clinical and patient focused nature of indexed literature. The most disease-specific MeSH term was 'Venous Thrombosis' (182 occurrences, TLS = 939), and 'Middle Aged' (215 occurrences, TLS = 1,386) and 'Aged' (173 occurrences, TLS = 1,148) had a high number of occurrences, reflecting a high weight on older adult populations, as per established epidemiology of DVT. Retrospective Studies (n=114, TLS=735) and Risk Factors (n=122, TLS=751) were validated and showed that the methodological paradigm in the corpus was the observational and risk-stratification study designs. Top of the indexer-assigned and as author-assigned conceptual frameworks, both 'MeSH term' and 'most frequently assigned author keyword' viewpoints found 'Machine Learning' first, 105 times and 71 times, respectively (Table 4; Figure 3B). The overlapping thematic width of the entire literature on VTE was also captured in shared author keywords, such as ' deep vein thrombosis "(48 occurrences, TLS = 79) and ' venous thromboembolism" (48 occurrences, TLS = 84).The broader VTE literature was also represented in the shared author keywords, such as ' deep vein thrombosis "(48 occurrences, TLS = 79) and ' venous thromboembolism" (48 occurrences, TLS = 84). New appearing terms were 'COVID-19' (13 (15)), and ' natural language processing" (13 (23)), indicating growing research areas in coagulopathy in a pandemic and data extraction from clinical texts to support research on NLP, respectively. The terms 'deep learning" (15 occurrences, TLS = 20) and ' anticoagulation ' (12 occurrences, TLS = 6) further defined methodological and therapeutic areas, which are developing within the field.

MeSH Keyword	Occurrences	Total Link Strength	Author Keyword	Occurrences	Total Link Strength
Adult	161	1,023	Anticoagulation	12	6
Aged	173	1,148	Artificial Intelligence	47	70
Female	249	1,481	COVID-19	13	15
Humans	475	1,929	Deep Learning	15	20
Machine Learning	105	597	Deep Vein Thrombosis	48	79
Male	254	1,500	Deep Venous Thrombosis	18	27
Middle Aged	215	1,386	Machine Learning	71	89
Pulmonary Embolism	74	381	Natural Language Processing	13	23
Retrospective Studies	114	735	Pulmonary Embolism	39	70
Risk Assessment	67	461	Retinal Vein Occlusion	14	4
Risk Factors	122	751	Risk Assessment	9	19
Tomography, X-Ray Computed	85	385	Risk Factors	12	19
Treatment Outcome	60	334	Thrombosis	25	31
Venous Thromboembolism	77	360	Venous Thromboembolism	48	84
Venous Thrombosis	182	939	Venous Thrombosis	13	14

Table 4. Top 15 MeSH terms and author keywords identified in the bibliometric analysis. Occurrences represent the total frequency of each term across indexed publications; total link strength reflects the cumulative co-occurrence network connectivity derived from the VOSviewer analysis.

Author Keyword Co-occurrence Network and Thematic Clusters

'Machine learning',' ' deep vein thrombosis',' ' venous thromboembolism', and ' artificial intelligence ' constitute the core of the keyword co-occurrence network, each exhibiting high betweenness centrality and dense inter-keyword linkages, reflecting their foundational role in defining the intellectual architecture of the field. Peripheral nodes, including ' natural language processing',' ' deep learning', and 'COVID-19', represent emerging thematic satellites with increasing co-occurrence connectivity, indicative of research trajectories gaining conceptual momentum at the field's frontier (Figure 3A). Keyword density mapping further corroborates these findings, identifying ' machine learning',' 'DVT', and ' venous thromboembolism ' as the highest-frequency research hotspots, with rising thermal weight observed for ' natural language processing ' and ' deep learning ' in more recent publication strata (Figure 3E).

Thematic Evolution and Emerging Research Directions

Earlier publications in this corpus predominantly concentrated on conventional risk factor identification and Doppler ultrasonography-based DVT diagnosis; however, the later temporal stratum reveals a decisive pivot toward predictive modeling, electronic health record (EHR)-based machine learning, and multimodal AI frameworks integrating imaging with laboratory parameters. Natural language processing for automated extraction of DVT-related clinical narratives from EHRs has emerged as a rapidly growing subdomain, as has AI-assisted risk stratification in the context of COVID-19-associated coagulopathy. Deep learning applied to venous duplex ultrasound interpretation and CT pulmonary angiography classification represents a further burgeoning frontier, reflecting the increasing availability of annotated imaging datasets (Figure 3C). Collectively, these trends indicate a field transitioning from descriptive, retrospective ML applications toward prospective, multimodal, and real-time AI-assisted tools for DVT detection, risk prediction, and anticoagulation optimization.

Citation Analysis and Highly Cited Publications

Citation network analysis revealed that foundational studies on VTE risk scoring, including adaptations of the Wells criteria and Padua prediction score, alongside landmark machine learning prediction models, constitute the most heavily cited nodes in the corpus, reflecting their role as methodological anchors for subsequent AI-driven research. The distribution of citations is markedly skewed, with a small number of seminal publications accumulating disproportionately high citation counts, a pattern consistent with the Matthew effect in scientific citation dynamics (Figure 3D).

Journal Analysis

The bibliometric corpus spans a broad range of peer-reviewed journals, reflecting the interdisciplinary nature of AI-DVT research. High-impact journals in hematology, vascular medicine, and thrombosis accommodated the majority of clinically oriented studies, whereas computational medicine and biomedical informatics outlets absorbed algorithmic and methodology-focused contributions. Journals in radiology and medical imaging published substantive work on AI-enhanced CT venography and duplex ultrasonography. The dispersal of publications across multiple disciplinary platforms without a single dominant journal cluster confirms that AI-DVT research has not yet coalesced around a dedicated publication venue, with outputs distributed across clinical, methodological, and translational journals in a pattern typical of nascent, cross-disciplinary fields.

Figure 3. Keyword, Citation, and Thematic Mapping Analyses. (A) Co-occurrence network of author keywords in artificial intelligence and deep vein thrombosis literature, with node size proportional to occurrence frequency and edge thickness reflecting co-occurrence strength. (B) MeSH term network visualization demonstrating major research clusters and inter-term connectivity. (C) Thematic evolution map highlighting temporal shifts in research priorities and emerging topics across the study period. (D) Citation network analysis of highly influential publications, with node size proportional to the citation count. (E) Density visualization of frequently occurring keywords and research hotspots, with color intensity representing the term frequency.

DISCUSSION

This bibliometric analysis provides a comprehensive cartography of the evolving scientific landscape at the intersection of artificial intelligence and deep vein thrombosis research. The accelerating publication trajectory, dominance of machine learning as a unifying methodological keyword, geographic concentration of output in North American and Western European institutions, and emergence of natural language processing and COVID-19-associated thrombosis as frontier themes collectively reflect a field undergoing rapid epistemic transition one that carries substantial scientific, clinical, and policy implications. Interpreting these patterns in the context of prior bibliometric literature on cardiovascular and thromboembolic disease reveals both the distinctiveness and predictable developmental arc of AI-DVT scholarship.

Exponential Growth and Historical Precedent

The progressive acceleration in annual publications observed in this analysis is consistent with bibliometric trends documented in adjacent domains, including AI applications in atrial fibrillation,[5] pulmonary embolism,[6] and broader cardiovascular risk prediction [7]. Price's law of exponential growth in scientific literature, wherein output doubles approximately every 10–15 years in maturing biomedical fields, appears to be operating at a compressed timescale in AI-DVT research, likely catalyzed by three convergent forces: the widespread availability of large-scale electronic health record datasets, the democratization of open-source machine learning frameworks (scikit-learn, TensorFlow, PyTorch), and the institutional prioritization of predictive analytics in value-based healthcare delivery [8,9].The citation accumulation tracked publication growth commensurately suggests that this expansion represents genuine scientific engagement rather than bibliometric inflation, a distinction of particular importance given documented concerns about low-quality AI publications in clinical medicine [10].

Interpretation of Author and Institutional Dominance

The concentration of high-output authorship within a relatively compact collaborative cluster, most prominently around the University of Maryland system, is a recognized feature of early-phase interdisciplinary fields, in which foundational work tends to originate from a small number of methodologically equipped groups before diffusing to a broader investigator base [11]. The high total link strength values of Lal, Brajesh K, and Mayorga-Carlin, Minerva (TLS = 36 each) are consistent with the existence of a tightly networked research program rather than independent parallel investigations, raising the possibility that a significant proportion of the indexed output derives from a single programmatic grant or institutional collaboration. This degree of author-level concentration, while productive, carries the attendant risk of methodological homogeneity within a literature still defining its own best practices for model development, validation, and reporting [12]. The divergence between high document counts and near-zero TLS values for authors such as Patell, Rushad (TLS = 3) and Li, Ang (TLS = 3) may reflect contributions from clinically oriented investigators working outside the dominant network, a heterogeneity that, if structurally supported through cross-disciplinary training, could broaden the field's methodological and clinical diversity.

Geographic Disparities and the Global Equity Gap

The predominance of U.S. and U.K. institutions in this corpus reflects a structural inequity that has been consistently documented across AI-health bibliometric analyses [13–15]. Low- and middle-income countries (LMICs), where DVT incidence may be underrecognized and clinical risk stratification tools are frequently inaccessible, remain almost entirely absent from the research landscape captured here. The sole exception, PGIMER, Chandigarh, India, contributed three publications with zero collaborative link strength, suggesting that Indian contributions occurred in research isolation rather than as part of integrated international networks. This is particularly consequential given the evidence that DVT epidemiology, thrombotic risk factor profiles, and anticoagulation access differ substantially across global regions, and that AI models trained predominantly on North American and European electronic health record (EHR) data may perform poorly when deployed in LMIC healthcare settings.[11] Addressing this gap requires deliberate research equity strategies, including international funding mechanisms, South-South collaboration frameworks, and LMIC-inclusive dataset design for model development and external validation. The absence of representation from Sub-Saharan Africa, Latin America, and Southeast Asia is a critical research lacuna that future initiatives including WHO digital health programs and NIH Fogarty International Center partnerships should prioritize.

Evolution of Research Focus: From Risk Scoring to Multimodal AI

The temporal evolution of thematic clusters captured in the keyword and MeSH analyses reflects a discernible shift in the field's intellectual preoccupations. The early dominance of terms such as ' retrospective studies "(114 occurrences), ' risk factors" (122 occurrences), and ' risk assessment "(67 occurrences) aligns with an initial phase focused on adapting established clinical scoring systems–Wells criteria, Caprini score, and Padua prediction model–to machine learning architectures, often using administrative or claims databases [16,17]. More recent thematic strata reveal a decisive pivot toward predictive modeling using structured EHR data, imaging-integrated AI (CT venography, duplex ultrasonography), and natural language processing for unstructured clinical text mining, a trajectory consistent with the broader maturation of clinical AI from proof-of-concept studies toward implementation-oriented frameworks [18]. The emergence of ' deep learning "(15 occurrences, TLS = 20) and ' natural language processing" (13 occurrences, TLS = 23) as author keywords, despite their modest absolute frequencies, likely underestimates their current research footprint, given the well-established lag between publication date and bibliometric indexing.

COVID-19 as a Catalytic Theme

The appearance of COVID-19 (13 occurrences, TLS = 15) as an emerging author keyword is scientifically significant beyond its bibliometric weight. SARS-CoV-2 infection is associated with a hypercoagulable state characterized by endotheliopathy, platelet hyperactivation, and dysregulated thrombin generation, substantially elevating the risk of DVT and pulmonary embolism in hospitalized patients [19]. The pandemic served as a natural experiment, generating large, well-characterized thrombotic event datasets that catalyzed the rapid development and validation of AI-based VTE risk prediction tools in critically ill populations. This COVID-19–VTE AI literature, while nascent in the indexed corpus, signals an important methodological and clinical crossover: models developed during the pandemic may provide transferable architectures for AI-based DVT risk stratification in non-COVID critically ill and surgical patients, where prophylaxis decisions currently rely on clinician judgment and static scoring tools that lack dynamic updating capability.

Clinical and Policy Implications

The predominance of retrospective, single-institution machine learning studies inferred from the high frequency of 'Retrospective Studies' as a MeSH descriptor reflects a field still largely in Phase I of the AI translation pipeline, generating promising models that have yet to be subjected to prospective, multicenter external validation [10,12]. For AI-DVT tools to achieve clinical integration, this pipeline must advance toward prospective trials evaluating whether AI-driven risk stratification improves DVT prophylaxis rates, reduces incidence, or shortens time-to-diagnosis without increasing bleeding complications from over-anticoagulation. Regulatory pathways, particularly the FDA's Software as a Medical Device (SaMD) framework and the European Union Medical Device Regulation (MDR 2017/745) demand evidence standards that the existing retrospective literature cannot satisfy [20].The low frequency of 'Anticoagulation' as an author keyword (12 occurrences, TLS = 6) is especially notable in this context: it suggests that existing AI research has concentrated heavily on DVT detection and risk prediction, while AI-assisted anticoagulation management including dosing optimization, drug-drug interaction flagging, and duration decision support remains critically underexplored. Given that anticoagulation-related adverse events constitute a leading cause of preventable iatrogenic harm, this represents a high-priority gap for future research and health technology development.

Underexplored Areas and Future Research Priorities

Several substantive research gaps emerge from this bibliometric analysis. First, the relative absence of pediatric DVT in the keyword landscape despite emerging evidence that venous thromboembolism in children represents a growing clinical burden, particularly in the context of central venous catheterization and systemic illness, reflects a lack of AI tool development tailored to pediatric thrombosis risk profiles [21].Second, AI applications in post-thrombotic syndrome prediction and long-term anticoagulation duration optimization remain underrepresented despite their substantial impact on patient quality of life and healthcare utilization. Third, explainability and algorithmic fairness, critical considerations for clinical AI deployment, are absent from the keyword landscape, suggesting that the field has not yet systematically engaged with the interpretability requirements necessary for clinician trust and regulatory approval. Fourth, the low link strength of 'Anticoagulation' as an author keyword signals that treatment decision support, beyond prediction, has been neglected. Future research should prioritize (i) multicenter prospective validation studies with prespecified primary outcomes; (ii) AI model development on LMIC-derived datasets; (iii) fairness audits of existing DVT prediction models across demographic subgroups; (iv) integration of AI tools within clinical decision support systems using interoperable FHIR-based EHR architectures; and (v) health economic evaluations of AI-assisted DVT management pathways.

Comparison with Bibliometric Analyses in Related Fields

This analysis shares structural features with bibliometric studies of AI in pulmonary embolism [6], atrial fibrillation [5], and stroke [22], including exponential publication growth, North American–European institutional dominance, machine learning as the central keyword cluster, and an emerging transition from diagnostic to prognostic AI applications. However, the DVT field appears to lag behind pulmonary embolism AI research in imaging-based deep learning, likely because CT pulmonary angiography provides a more readily annotatable imaging substrate than venous duplex ultrasonography, which is operator-dependent, anatomically complex, and less amenable to automated annotation pipelines that have driven radiology AI development [18]. Closing this gap will require investment in standardized duplex ultrasound dataset curation, multi-institutional image-sharing agreements, and deep-learning architectures adapted for operator-variable acquisition conditions.

STRENGTHS AND LIMITATIONS

Strengths

This study has several methodological strengths that enhance the validity and reproducibility of its findings. The use of a systematic, pre-specified bibliometric methodology ensures transparency and replicability, consistent with established reporting frameworks for bibliometric research [23]. The combination of multiple analytical tools, VOSviewer for network visualization and co-occurrence mapping, and bibliometric analysis software for publication trend quantification, enabled triangulation of findings across complementary analytical lenses, reducing the likelihood of framework-specific artifacts. The inclusion of both MeSH terms and author keywords in the thematic analysis captured both indexer-assigned and investigator-defined conceptual structures, providing a more complete representation of the field's intellectual architecture than either approach alone. The deployment of total link strength as a metric of collaborative embedding rather than raw co-authorship frequency provides a more nuanced measure of network connectivity, appropriately weighting sustained versus incidental co-authorship. The comprehensive coverage of the analysis across author, institutional, country, journal, keyword, and citation dimensions ensures a multidimensional characterization of the field that single-metric analyses cannot achieve.

Database Dependence and Coverage Limitations

A principal limitation of this study is its dependence on a single or primary bibliometric database (e.g., Web of Science or Scopus), each of which applies its own journal-selection criteria, indexing coverage rules, and citation normalization protocols. Studies indexed exclusively in PubMed/MEDLINE, Embase, or regional databases not captured by the primary platform may have been systematically excluded, potentially underrepresenting the contributions of journals in non-Anglophone research traditions. Prior comparative analyses have demonstrated that the Web of Science and Scopus show differential coverage of journals across disciplines and geographic regions, with Scopus offering broader coverage of European and Asian journals [24]. Investigators seeking to replicate or extend this analysis should consider multi-database approaches to maximize coverage, acknowledging the attendant challenges of deduplication across platforms.

Language Restrictions and Publication Bias

The restriction to English-language publications is standard practice in bibliometric analyses of clinical AI research, introducing a systematic language bias that disproportionately disadvantages researchers publishing in non-English scientific literature. Significant AI-DVT research conducted in Chinese, Spanish, German, and Japanese medical journals may have been excluded, and the observed geographic concentration of output in English-speaking countries may partly reflect this linguistic filter rather than true differences in research productivity. This limitation is particularly consequential for the interpretation of LMIC under-representation, as Chinese institutions are among the most prolific contributors to AI-health bibliometrics globally [13], and may have published extensively in Chinese-language outlets not captured by the analysis.

Citation Bias and Temporal Confounding

Citation counts are inherently time-dependent: older publications accumulate citations simply by virtue of their longer exposure window, independent of their intrinsic scientific impact. This temporal confounding means that recently published studies, including those employing the most methodologically advanced deep learning and NLP approaches, are structurally disadvantaged in citation-based analyses relative to earlier foundational work [25]. Normalized citation metrics (e.g., field-normalized citation scores) partially mitigate this effect but were not consistently applied across all components of this analysis. Additionally, self-citation inflation, a recognized distortion in bibliometric analyses of small, tightly networked research communities such as this one, cannot be excluded and may have amplified the apparent citation centrality of core cluster authors.

Dynamic Nature of Bibliometric Databases

Bibliometric databases are dynamic entities: citation counts, document records, author affiliations, and keyword assignments are continuously updated. The findings reported here reflect a snapshot captured at the time of data extraction and will inevitably diverge from analyses conducted at later time points. This temporal instability is an intrinsic limitation of the bibliometric methodology and means that the numerical findings, particularly citation counts and link strengths, should be interpreted as period-specific estimates rather than fixed quantities [23]. Future analyses should report extraction dates explicitly and consider time-locked database snapshots where reproducibility is a primary concern.

Software-Related Limitations

Network visualizations and co-occurrence analyses were performed using VOSviewer, a widely validated and extensively cited bibliometric software. However, VOSviewer applies its own clustering algorithm (modularity-based community detection) and normalization approach (association strength normalization); thus, the resulting network topologies are sensitive to threshold parameters, including the minimum number of document co-occurrences required for keyword inclusion and the resolution parameter that governs the cluster granularity. Alternative software platforms (CiteSpace, Gephi, and Bibliometrix R package) may generate different network structures from identical underlying data, and the absence of multi-software sensitivity analyses is a limitation of this study [26]. Researchers interpreting co-occurrence network figures should understand that node placement, cluster boundaries, and edge weights are algorithm-dependent representations and not objective measurements of conceptual proximity.

Methodological Scope

This analysis is descriptive and hypothesis-generating rather than confirmatory; it identifies patterns in the published literature but cannot establish causal explanations for observed trends, nor can it assess the internal or external validity of the constituent studies. The quality, reproducibility, and clinical applicability of individual publications within the corpus are not evaluated, and the bibliometric prominence of a publication, as reflected in citation count or network centrality, does not necessarily correlate with methodological rigor or translational value. These caveats are intrinsic to the bibliometric methodology and reinforce the need for systematic reviews and meta-analyses of clinical AI performance in DVT as the field continues to mature.

CONCLUSION

This bibliometric analysis offers a comprehensive overview of the intersection of artificial intelligence (AI) and deep vein thrombosis (DVT) research. It highlights a significant increase in global scientific output, showcasing the integration of machine learning, deep learning, natural language processing, and predictive analytics into venous thromboembolism (VTE) research and clinical practice. Predominantly, the intellectual landscape is shaped by North American and Western European institutions, with machine learning-focused risk prediction and diagnostic modeling emerging as central themes.

The analysis reveals a shift from traditional retrospective risk assessment to innovative multimodal AI systems that utilize electronic health records, imaging data, and automated clinical text extraction. Prominent emerging research areas include COVID-19-related thrombosis prediction, deep learning for imaging interpretation, and AI-enabled prognostic stratification fields that hold considerable translational potential. Nonetheless, challenges remain, such as geographic disparities in research involvement, a lack of prospective multicenter validation studies, minimal emphasis on anticoagulation management, and inadequate attention to issues like explainability, fairness, and implementation science. Overall, AI-DVT research is in a critical developmental phase, moving beyond exploratory computational models toward clinically viable decision-support systems. Future advancements will necessitate international cooperation, multicenter studies, and external validation focused on fair data representation, transparent algorithms, and real-world clinical application to ensure the safety and effectiveness of AI-assisted thrombosis care.

References

[1] Stone J, Hangge P, Albadawi H, Wallace A, Shamoun F, Knuttien MG, et al. Deep vein thrombosis: pathogenesis, diagnosis, and medical management. Cardiovasc Diagn Ther. 2017 Dec;7(Suppl 3):S276–84. doi:10.21037/cdt.2017.09.01 PubMed PMID: 29399531; PubMed Central PMCID: PMC5778510.

[2] Puttarak K, Angchaisuksiri P, Boonyawat K. Delayed diagnosis and treatment of deep vein thrombosis - an underrecognized factor for its related outcomes? Thromb J. 2025 Sep 30;23:85. doi:10.1186/s12959-025-00769-x PubMed PMID: 41029651; PubMed Central PMCID: PMC12487182.

[3] Crisan DN, Cut TG, Herlo LF, Ivanovic N, Herlo A, Alexandrescu L, et al. Artificial Intelligence in Venous Thromboembolism Prevention: A Narrative Review of Machine Learning, Deep Learning, and Natural Language

Processing. J Cardiovasc Dev Dis. 2026 Mar 6;13(3):119. doi:10.3390/jcdd13030119 PubMed PMID: 41892708; PubMed Central PMCID: PMC13027222.

[4] Kumar R. Bibliometric Analysis: Comprehensive Insights into Tools, Techniques, Applications, and Solutions for Research Excellence. Spectrum of Engineering and Management Sciences. 2025 Jan 5;3:45–62. doi:10.31181/sems31202535k

[5] Siontis KC, Noseworthy PA, Attia ZI, Friedman PA. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nat Rev Cardiol. 2021 Jul;18(7):465–78. doi:10.1038/s41569-020-00503-2 PubMed PMID: 33526938; PubMed Central PMCID: PMC7848866.

[6] Zhou Y, Xu W, Zeng Y, Li H, Liu Z, Wang T, et al. Global research trends of the application of artificial intelligence in bladder cancer since the 21st century: a bibliometric analysis. Front Oncol. 2023 Nov 29;13:1227152. doi:10.3389/fonc.2023.1227152 PubMed PMID: 38094602; PubMed Central PMCID: PMC10718619.

[7] He S, Shen Z. Research Hotspots and Prospects of Artificial Intelligence in Cardiovascular Disease: A Bibliometric Analysis. Journal of Multidisciplinary Healthcare. 2025 Dec 23;18(0):8209–23. doi:10.2147/JMDH.S553225

[8] Derek J. de Solla Price. Little Science, Big Science by Derek J. de Solla Price (1965-07-01) [Internet]. Columbia University Press; 1963 [cited 2026 May 20]. 134 p. Available from: http://archive.org/details/littlesciencebig0000dere

[9] Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. Nat Med. 2022 Jan;28(1):31–8. doi:10.1038/s41591-021-01614-0

[10] Nagendran M, Chen Y, Lovejoy CA, Gordon AC, Komorowski M, Harvey H, et al. Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies. BMJ. 2020 Mar 25;368:m689. doi:10.1136/bmj.m689 PubMed PMID: 32213531; PubMed Central PMCID: PMC7190037.

[11] Klavans R, Boyack KW. Which Type of Citation Analysis Generates the Most Accurate Taxonomy of Scientific and Technical Knowledge? Journal of the Association for Information Science and Technology. 2017;68(4):984–98. doi:10.1002/asi.23734

[12] Collins GS, Dhiman P, Andaur Navarro CL, Ma J, Hooft L, Reitsma JB, et al. Protocol for development of a reporting guideline (TRIPOD-AI) and risk of bias tool (PROBAST-AI) for diagnostic and prognostic prediction model studies based on artificial intelligence. BMJ Open. 2021 Jul 9;11(7):e048008. doi:10.1136/bmjopen-2020-048008 PubMed PMID: 34244270; PubMed Central PMCID: PMC8273461.

[13] Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, et al. Artificial intelligence in healthcare: past, present and future. Stroke Vasc Neurol. 2017 Dec;2(4):230–43. doi:10.1136/svn-2017-000101 PubMed PMID: 29507784; PubMed Central PMCID: PMC5829945.

[14] Yusuf M, Atal I, Li J, Smith P, Ravaud P, Fergie M, et al. Reporting quality of studies using machine learning models for medical diagnosis: a systematic review. BMJ Open. 2020 Mar 23;10(3):e034568. doi:10.1136/bmjopen-2019-034568 PubMed PMID: 32205374; PubMed Central PMCID: PMC7103817.

[15] Gianfrancesco MA, Tamang S, Yazdany J, Schmajuk G. Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data. JAMA Intern Med. 2018 Nov 1;178(11):1544–7. doi:10.1001/jamainternmed.2018.3763 PubMed PMID: 30128552; PubMed Central PMCID: PMC6347576.

[16] Wells PS, Anderson DR, Bormanis J, Guy F, Mitchell M, Gray L, et al. Value of assessment of pretest probability of deep-vein thrombosis in clinical management. Lancet. 1997 Dec 20;350(9094):1795–8. doi:10.1016/S0140-6736(97)08140-3 PubMed PMID: 9428249.

[17] Barbar S, Noventa F, Rossetto V, Ferrari A, Brandolin B, Perlati M, et al. A risk assessment model for the identification of hospitalized medical patients at risk for venous thromboembolism: the Padua Prediction Score. J Thromb Haemost. 2010 Nov;8(11):2450–7. doi:10.1111/j.1538-7836.2010.04044.x PubMed PMID: 20738765.

[18] Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019 Jan;25(1):44–56. doi:10.1038/s41591-018-0300-7

[19] Bikdeli B, Madhavan MV, Jimenez D, Chuich T, Dreyfus I, Driggin E, et al. COVID-19 and Thrombotic or Thromboembolic Disease: Implications for Prevention, Antithrombotic Therapy, and Follow-Up: JACC State-of-the-Art Review. J Am Coll Cardiol. 2020 Jun 16;75(23):2950–73. doi:10.1016/j.jacc.2020.04.031 PubMed PMID: 32311448; PubMed Central PMCID: PMC7164881.

[20] US Food and Drug Administration. Software as a Medical Device (SaMD) Action Plan [Internet]. 2021 Jan. Available from: www.fda.gov

[21] Mahajerin A, Croteau SE. Epidemiology and Risk Assessment of Pediatric Venous Thromboembolism. Front Pediatr. 2017 Apr 10;5:68. doi:10.3389/fped.2017.00068 PubMed PMID: 28443269; PubMed Central PMCID: PMC5385336.

[22] Saba L, Biswas M, Kuppili V, Cuadrado Godia E, Suri HS, Edla DR, et al. The present and future of deep learning in radiology. Eur J Radiol. 2019 May;114:14–24. doi:10.1016/j.ejrad.2019.02.038 PubMed PMID: 31005165.

[23] Donthu N, Kumar S, Mukherjee D, Pandey N, Lim WM. How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research. 2021 Sep 1;133:285–96. doi:10.1016/j.jbusres.2021.04.070

[24] Mongeon P, Paul-Hus A. The journal coverage of Web of Science and Scopus: a comparative analysis. Scientometrics. 2016 Jan 1;106(1):213–28. doi:10.1007/s11192-015-1765-5

[25] Garfield E. Citation Analysis as a Tool in Journal Evaluation. Science. 1972 Nov 3;178(4060):471–9. doi:10.1126/science.178.4060.471

[26] van Eck NJ, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics. 2010 Aug 1;84(2):523–38. doi:10.1007/s11192-009-0146-3

Table 1: Top 10 Contributing Authors in Artificial Intelligence–Driven Deep Vein Thrombosis Research Based on Document Count and Total Link Strength

Author	**Documents**	**Total Link Strength**
Hayssen, Hilary	5	34
Lal, Brajesh K	6	36
Lam, Barbara D	6	6
Li, Ang	6	3
Mayorga-Carlin, Minerva	6	36
Nguyen, Phuong	5	34
Patell, Rushad	5	3
Sahoo, Shalini	5	34

Siddiqui, Tariq	5	34
Sorkin, John D	5	30
Yesha, Yelena	5	34

Table 2: Most Productive Institutions and Organizational Collaboration Networks in Deep Vein Thrombosis Research

Organization	Documents	Total Link Strength
Bristol Myers Squibb Pharmaceutical Ltd, Uxbridge, Uk	2	4
Cardiology Clinical Academic Group, Molecular & Clinical Sciences Research Institute, St. George's University Of London, London, Uk	2	4
Department Of Computer Science, University Of Miami, Miami, Fl	5	7
Department Of Haematological Medicine, Guys And St Thomas' Nhs Foundation Trust, King's College London, London, Uk	2	4
Department Of Internal Medicine, Hospital Universitario De Fuenlabrada, 28942 Madrid, Spain	2	4
Department Of Internal Medicine, Hospital Universitario Infanta Leonor, 28031 Madrid, Spain	2	4
Department Of Medicine, Universidad Complutense De Madrid, 28040 Madrid, Spain	2	4
Department Of Medicine, University Of Maryland School Of Medicine, Baltimore, Md	5	8
Department Of Radiodiagnosis, Postgraduate Institute Of Medical Education And Research, Chandigarh, India	3	0
Department Of Surgery, University Of Maryland, Baltimore, Md	4	7

Table 4: Top 15 MeSH Terms and Author Keywords Identified in the Bibliometric Analysis

MeSH keyword	occurrences	total link strength	Author keyword	occurrences	total link strength
Adult	161	1023	Anticoagulation	12	6
Aged	173	1148	Artificial Intelligence	47	70
Female	249	1481	Covid-19	13	15
Humans	475	1929	Deep Learning	15	20
Machine Learning	105	597	Deep Vein Thrombosis	48	79
Male	254	1500	Deep Venous Thrombosis	18	27
Middle Aged	215	1386	Machine Learning	71	89
Pulmonary Embolism	74	381	Natural Language Processing	13	23

Retrospective Studies	114	735	Pulmonary Embolism	39	70
Risk Assessment	67	461	Retinal Vein Occlusion	14	4
Risk Factors	122	751	Risk Assessment	9	19
Tomography, X-Ray Computed	85	385	Risk Factors	12	19
Treatment Outcome	60	334	Thrombosis	25	31
Venous Thromboembolism	77	360	Venous Thromboembolism	48	84
Venous Thrombosis	182	939	Venous Thrombosis	13	14

Natural Resources for Human Health
eISSN: 2583-1194

Figure 1: Publication and Research Trend Analysis

Figure 1A :- Annual Scientific Production of Publications Related to Artificial Intelligence and Deep Vein Thrombosis

Figure 1B :- Growth Trend of Publications and Citations Over Time

Figure 1C :- Distribution of Publications by Research Domain and Subject Area

Figure 1D :-Temporal Evolution of Research Output in Venous Thromboembolism and Machine Learning Studies

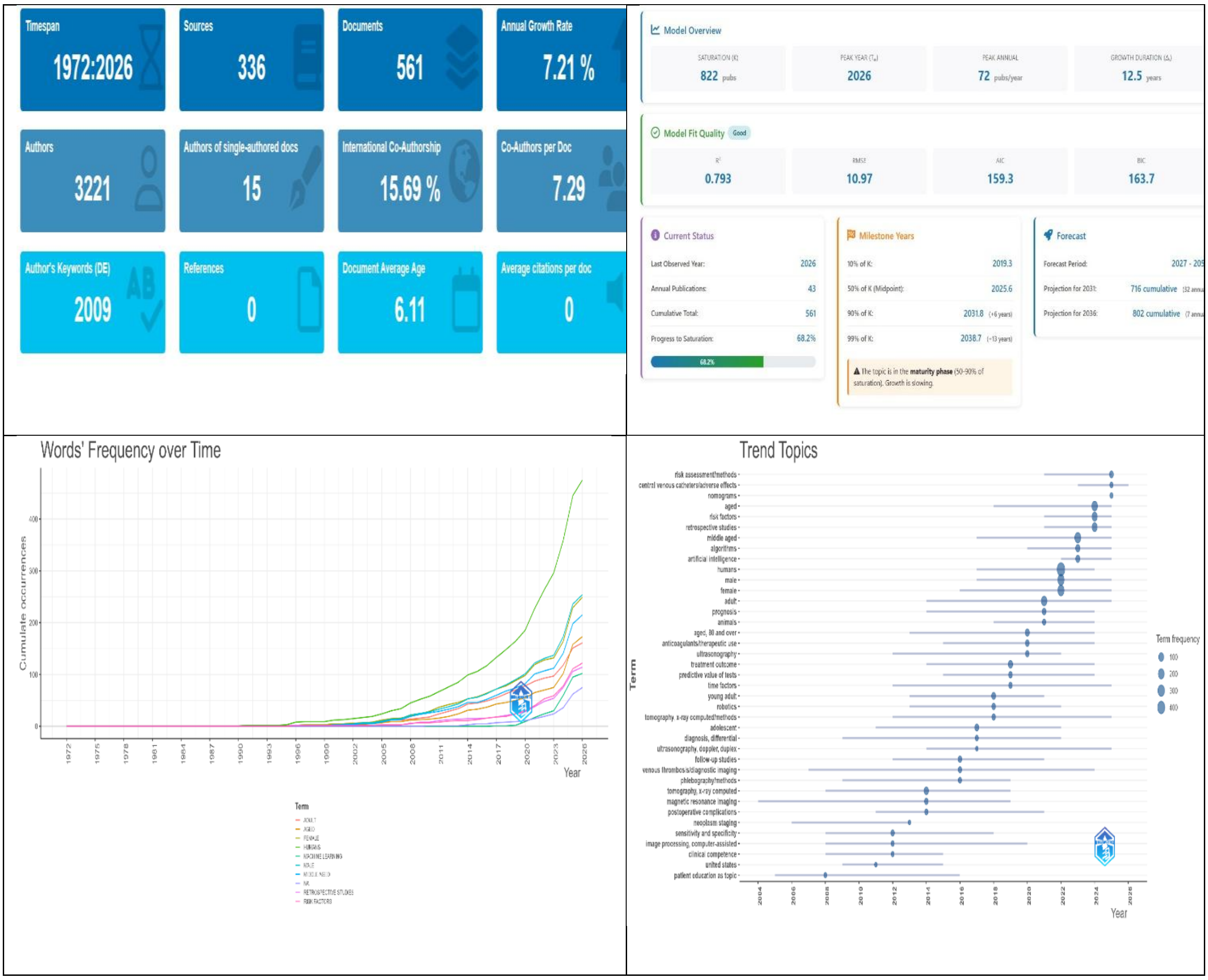


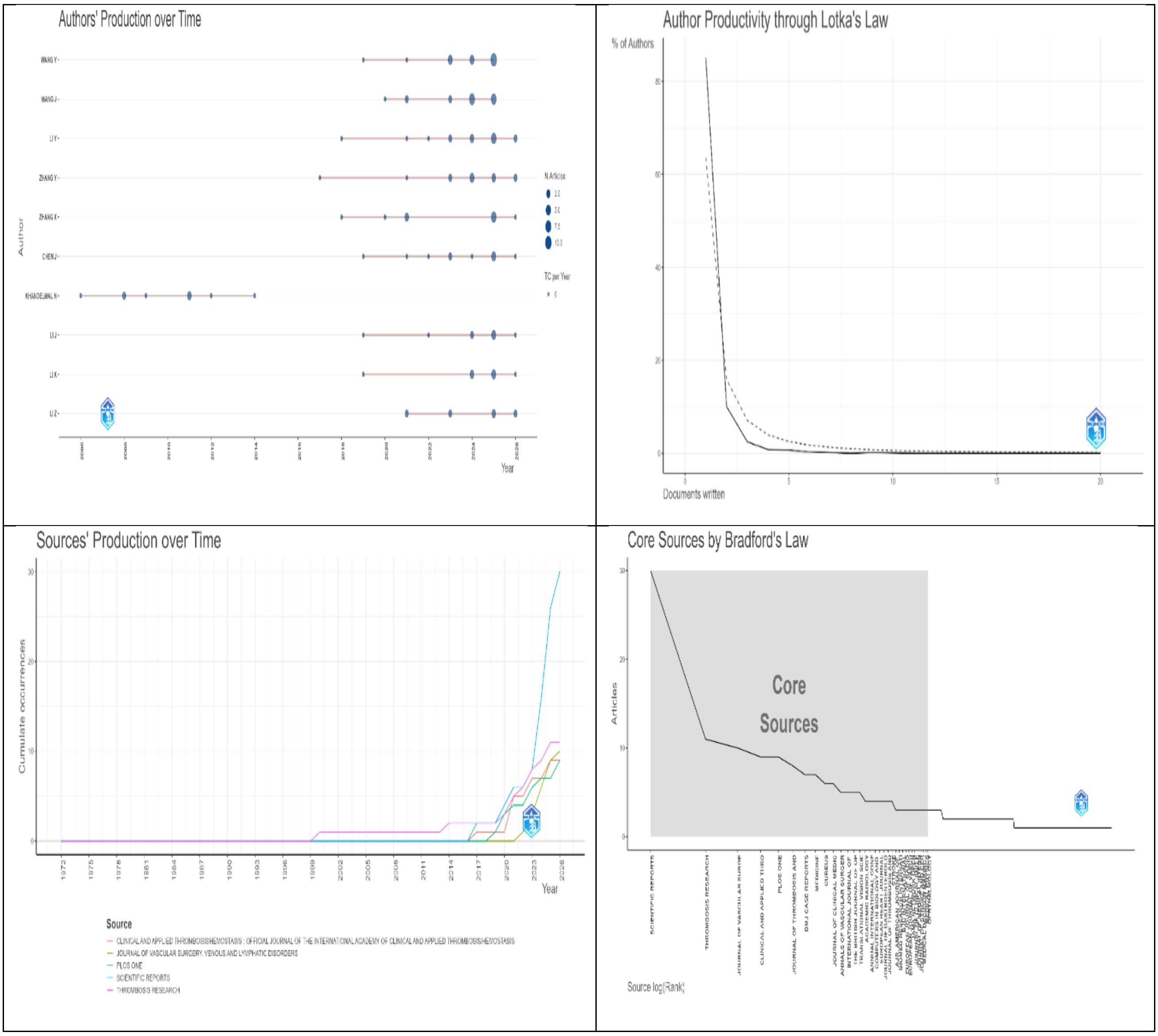
Figure 2: Author, Institutional, and Country Collaboration Networks

Figure 2A :- Co-authorship Network Visualization of Leading Authors in Deep Vein Thrombosis Research

Figure 2B :- Institutional Collaboration Network Among Major Research Organizations

Figure 2C :- Country-wise Scientific Collaboration Map in Artificial Intelligence–Based Venous Thromboembolism Research

Figure 2D:- Network Visualization of International Research Partnerships and Link Strengths



eISSN: 2583-1194

Figure 3: Keyword, Citation, and Thematic Mapping Analyses

Figure 3A :- Co-occurrence Network of Author Keywords in Artificial Intelligence and Deep Vein Thrombosis Literature

Figure 3B - MeSH Term Network Visualization Demonstrating Major Research Clusters

Figure 3C - Thematic Evolution Map Highlighting Emerging Research Trends and Topics

Figure 3D :- Citation Network Analysis of Highly Influential Publications in the Field

Figure 3E:- Density Visualization of Frequently Occurring Keywords and Research Hotspots