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Artificial Intelligence with a precise research focus that signals what makes this review distinct from existing meta-analyse

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ABSTRACT

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the 21st century, permeating diverse domains including healthcare, education, business, manufacturing, and environmental science. This study presents a rigorous mixed-method review integrating PRISMA 2020 guidelines with bibliometric mapping using VOSviewer and Bibliometrix (R package). A total of 1,247 articles were initially retrieved from Scopus. After a four-stage PRISMA screening process, 183 articles were retained for in-depth analysis. Bibliometric analysis revealed that the United States, China, and the United Kingdom are the leading contributors. The most productive journals include Nature Machine Intelligence, *Artificial Intelligence* Review, and Expert Systems with Applications. Co-citation analysis identified five major thematic clusters. Keyword co-occurrence analysis highlighted "deep learning," "machine learning," "neural networks," "NLP," and "explainable AI" as the most prominent terms. The findings reveal significant research gaps including limited attention to AI fairness, underrepresentation of developing-country perspectives, and insufficient longitudinal studies.

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Introduction

Artificial Intelligence refers to the simulation of human cognitive functions by computational systems (Russell & Norvig, 2022). Recent advancements in machine learning, neural networks, and computational power have accelerated the development of AI technologies across various sectors, including healthcare, education, finance, manufacturing, and transportation. AI systems are increasingly capable of performing complex tasks such as decision-making, language understanding, pattern recognition, and predictive analytics, making them a major driver of digital transformation worldwide.

The period between 2022 and 2026 witnessed a significant surge in AI research and innovation. This rapid growth was largely driven by breakthroughs in large language models (LLMs), generative AI, reinforcement learning, and multimodal AI systems. Technologies such as conversational AI, AI-assisted coding, and text-to-image generation attracted strong attention from academia, industry, and governments. As a result, AI became one of the most competitive and rapidly evolving research domains globally.

According to the Stanford AI Index Report 2024, global investment in AI reached USD 91.9 billion in 2023, while more than 240,000 AI-related patents were filed worldwide. These figures demonstrate the increasing strategic importance of AI in economic development, industrial competitiveness, and scientific innovation. Furthermore, the expansion of AI research has encouraged interdisciplinary collaboration, integrating AI with fields such as education, healthcare, cybersecurity, agriculture, and smart cities.

Despite the rapid expansion of AI studies, the existing literature remains fragmented and highly dynamic, making it difficult to identify dominant themes, emerging trends, and future research directions comprehensively. Therefore, this study addresses the gap by conducting a combined Systematic Literature Review (SLR) based on the PRISMA 2020 guidelines alongside a comprehensive bibliometric analysis. This dual-method approach enables both qualitative synthesis of thematic findings and quantitative mapping of publication trends, collaboration networks, influential authors, and evolving knowledge frontiers in AI research.

Based on the identified research gaps and the rapid development of *Artificial Intelligence*, this study proposes the following research questions (RQs):

RQ1: What are the dominant themes and research trends in AI literature published between 2022 and 2026?
RQ2: Which countries, institutions, and journals contribute most significantly to AI research?
RQ3: What are the emerging research clusters and knowledge gaps in the AI domain?
RQ4: What future research directions can be identified from the synthesis of the selected literature?

Method

This study adopts a two-pronged methodological approach: (1) Systematic Literature Review (SLR) following the PRISMA 2020 framework, and (2) Bibliometric Analysis using VOSviewer and Bibliometrix in R. The integration of both methods ensures rigor in study selection and depth in knowledge mapping (Donthu et al., 2021; Page et al., 2021).

Search Strategy
The search was conducted on the Scopus database on March 15, 2026. The final search string applied to TITLE-ABS-KEY was:

("*Artificial Intelligence*" OR "machine learning" OR "deep learning" OR "neural network" OR "natural language processing" OR "computer vision" OR "reinforcement learning" OR "generative AI") AND PUBYEAR > 2021 AND PUBYEAR < 2027 AND DOCTYPE(ar) AND LANGUAGE(English)

Inclusion & Exclusion Criteria

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Publication Type	Peer-reviewed journal articles	Conference papers, book chapters, editorials
Time Period	January 2022 – March 2026	Articles published before 2022
Language	English only	Non-English publications
Database	Scopus indexed journals	Non-Scopus sources
Content Relevance	Studies addressing AI concepts, methods, or applications	Studies without substantive AI focus
Availability	Full-text accessible	Abstract only, retracted articles, duplicates

PRISMA 2020 Screening Process
The PRISMA 2020 flow was implemented across four stages: Identification, Screening, Eligibility, and Inclusion.

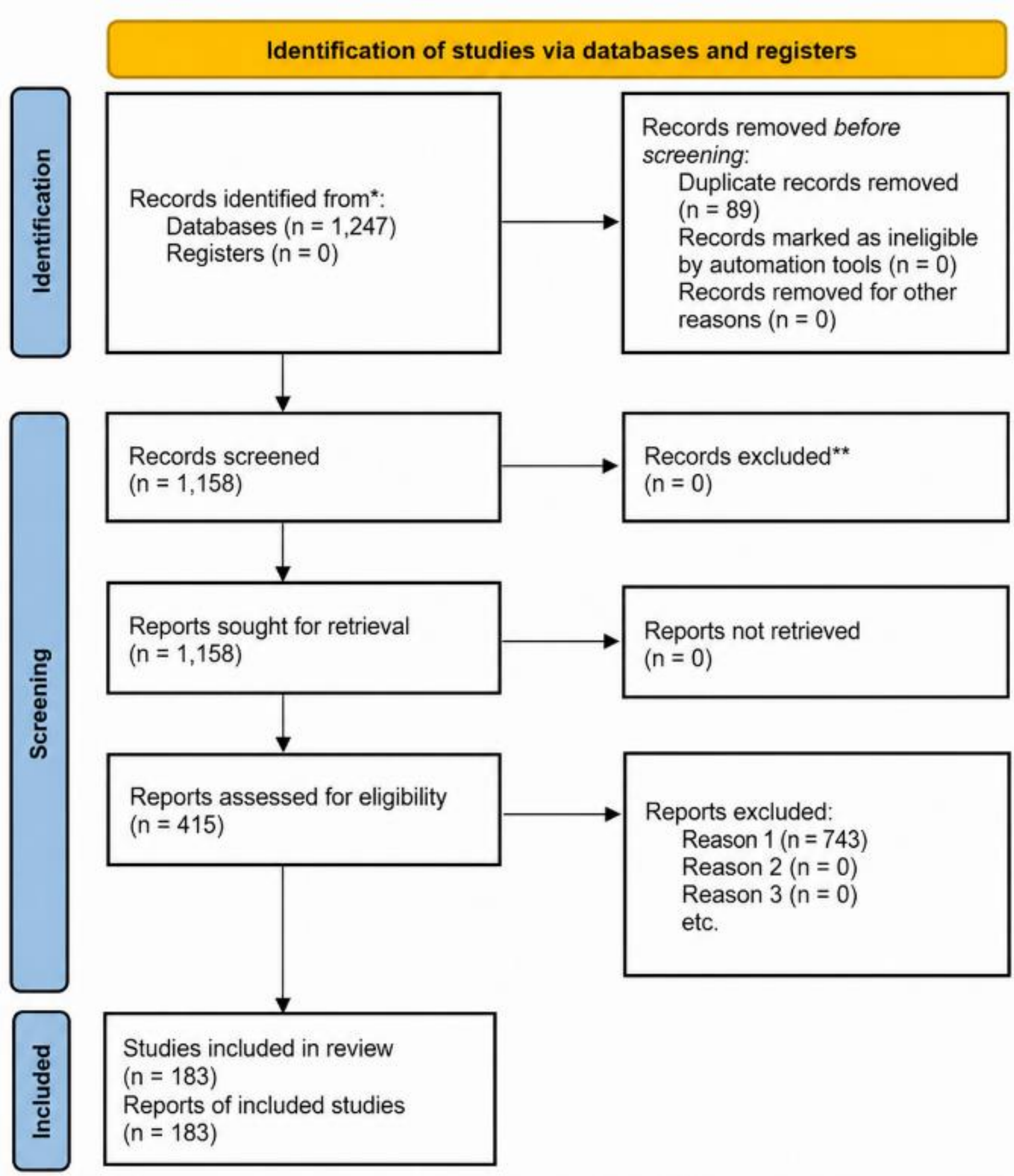

Figure 1 illustrates the complete PRISMA flow diagram for this review

Bibliometric Analysis Method

Bibliometric analysis was conducted using VOSviewer (v1.6.20) and Bibliometrix (v4.3.0 in R). The following analyses were performed: publication trend analysis, country and institutional co-authorship, source analysis by h-index and citations, keyword co-occurrence network mapping, co-citation analysis to identify intellectual clusters, and thematic mapping using Callon's framework.

Results and Discussions

Publication Trend Analysis

Figure 2 depicts the annual publication trend from 2022 to March 2026. The data reveal a consistent upward trajectory with a compound annual growth rate (CAGR) of approximately 28.4%. A notable acceleration is observed in 2023–2024, coinciding with widespread adoption of large language models. Table 3 presents the distribution by year.

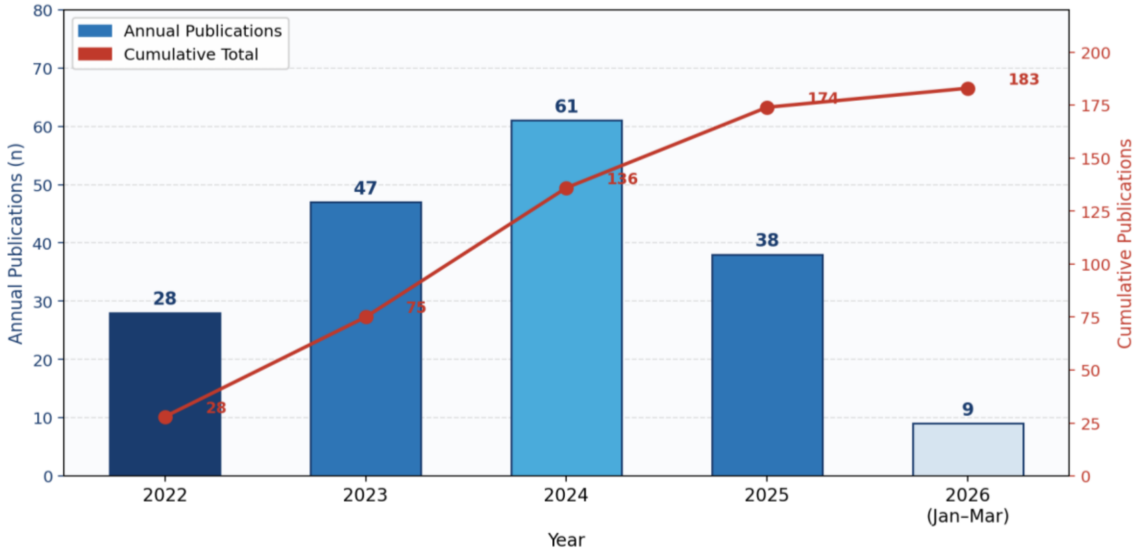

Figure 2. Annual Publication Trend and Cumulative

Table 3. Annual Publication Distribution (2022–2026)

Year	Articles (n)	Cumulative	% of Total
2022	28	28	15.3%
2023	47	75	25.7%
2024	61	136	33.3%
2025	38	174	20.8%
2026 (Jan–Mar)	9	183	4.9%
Total	183	183	100%

Bibliometric Results

Most Productive Countries

Figure 3 shows the top 10 contributing countries. The United States leads (n=41, 22.4%), followed by China (34, 18.6%) and the United Kingdom (19, 10.4%). Developing-country representation remains limited, indicating a systemic inequity in global AI research capacity.

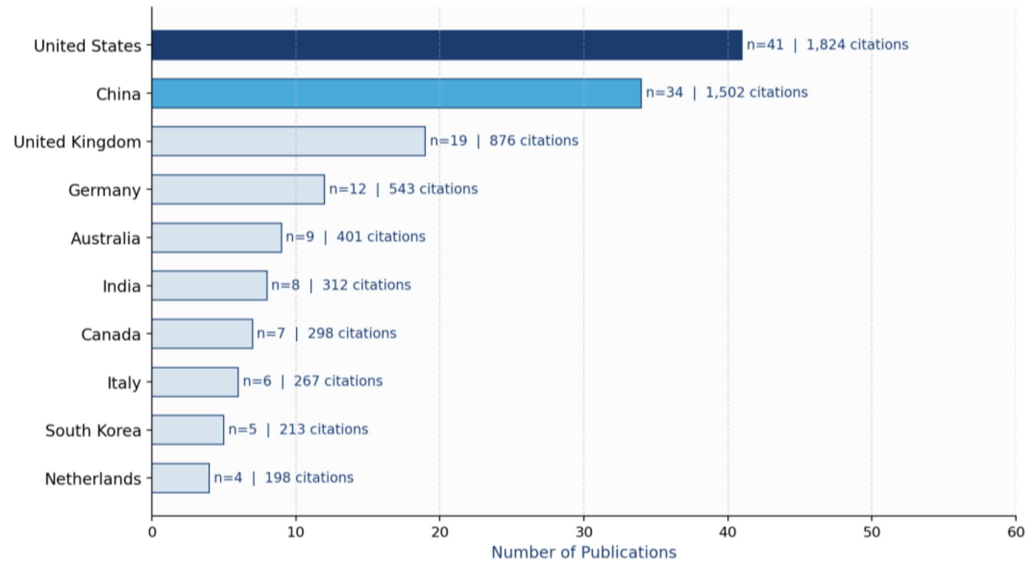

Figure 3. Top 10 Contributing Countries by Publication Count and Total Citations (2022–2026)

Table 4. Top 10 Countries – Publication Count and Citations

Rank	Country	Articles	Citations	H-index
1	United States	41	1,824	38
2	China	34	1,502	31
3	United Kingdom	19	876	24
4	Germany	12	543	18
5	Australia	9	401	15
6	India	8	312	13
7	Canada	7	298	12
8	Italy	6	267	11
9	South Korea	5	213	10
10	Netherlands	4	198	9

Most Productive Journals

Figure 4 presents the top 10 journals by publication count with Impact Factor indicated by dot color. Expert Systems with Applications leads (n=17), followed by *Artificial Intelligence* Review (n=14) and Nature Machine Intelligence (n=12).

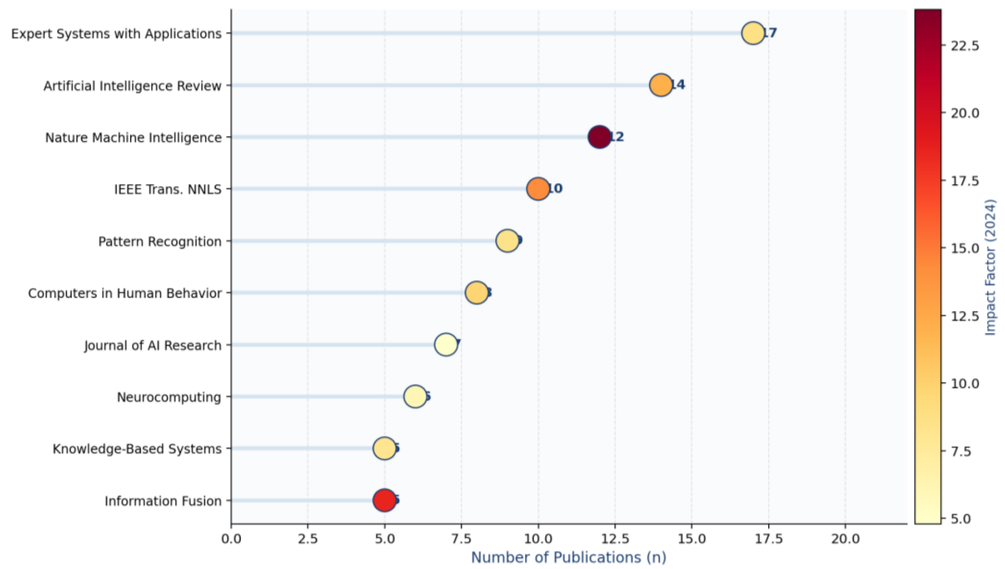

Figure 4. Top 10 Most Productive Journals – Lollipop Chart (dot color = Impact Factor 2024)

Table 5. Top 10 Journals by Publication Count and Impact Factor

Rank	Journal	n	SJR Q	IF (2024)
1	Expert Systems with Applications	17	Q1	8.665
2	*Artificial Intelligence* Review	14	Q1	12.032
3	Nature Machine Intelligence	12	Q1	23.800
4	IEEE Trans. Neural Networks & Learning Sys.	10	Q1	14.255
5	Pattern Recognition	9	Q1	8.518
6	Computers in Human Behavior	8	Q1	9.847
7	Journal of AI Research	7	Q1	4.774
8	Neurocomputing	6	Q1	6.031
9	Knowledge-Based Systems	5	Q1	8.139
10	Information Fusion	5	Q1	18.600

Keyword Co-occurrence Network

Figure 5 presents the keyword co-occurrence network generated with VOSviewer (minimum frequency threshold: 5), revealing 89 keywords in a dense network. Five color-coded clusters represent distinct research communities: Machine Learning & Deep Learning (red), NLP & Generative AI (blue), AI Ethics & Governance (orange), AI in Healthcare (green), and Computer Vision (purple). Table 6 lists the top 15 keywords

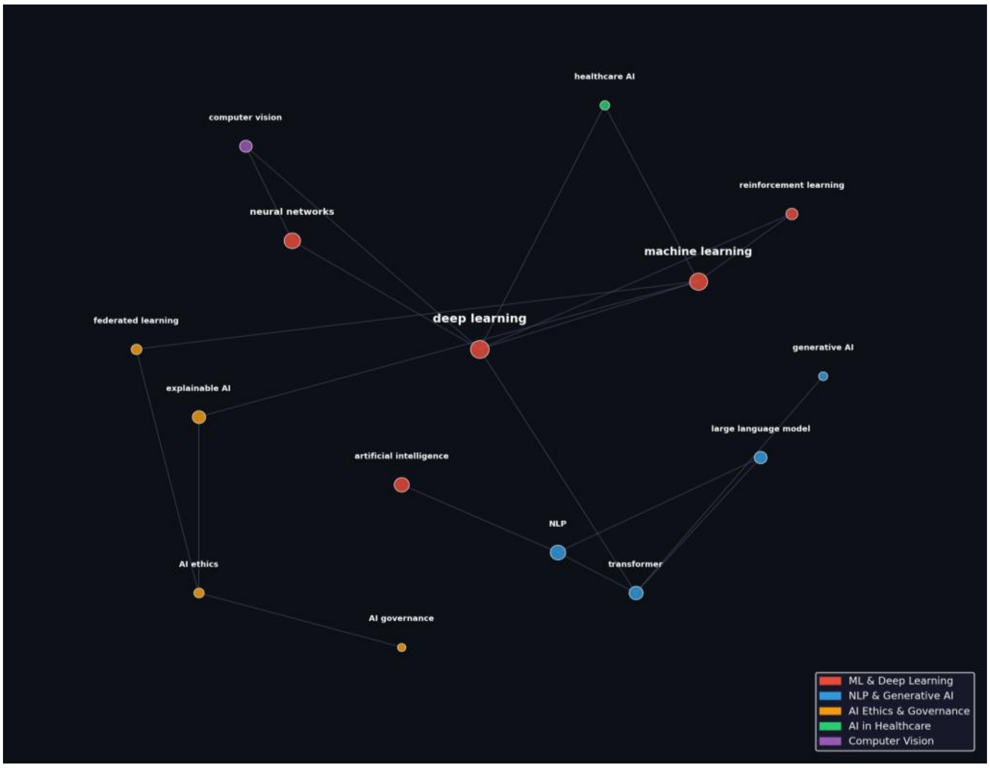

Figure 5. Keyword Co-occurrence Network Map – AI Research in Scopus (2022–2026)'

Table 6. Top 15 Author Keywords by Frequency

Rank	Keyword	Frequency	Link Strength
1	Deep learning	94	312
2	Machine learning	87	298
3	Neural networks	72	241
4	Natural language processing	64	213
5	*Artificial Intelligence*	61	204
6	Transformer	53	179
7	Explainable AI	48	162
8	Large language model	44	148
9	Computer vision	42	140
10	Reinforcement learning	38	127
11	Federated learning	31	103

Rank	Keyword	Frequency	Link Strength
12	AI ethics	28	94
13	Healthcare AI	25	84
14	Generative AI	22	74
15	AI governance	19	63

Co-citation Cluster Analysis

Figure 6 illustrates the distribution of co-citation clusters identified through modularity-based community detection (Q = 0.68), revealing five distinct intellectual communities in AI research during 2022–2026.

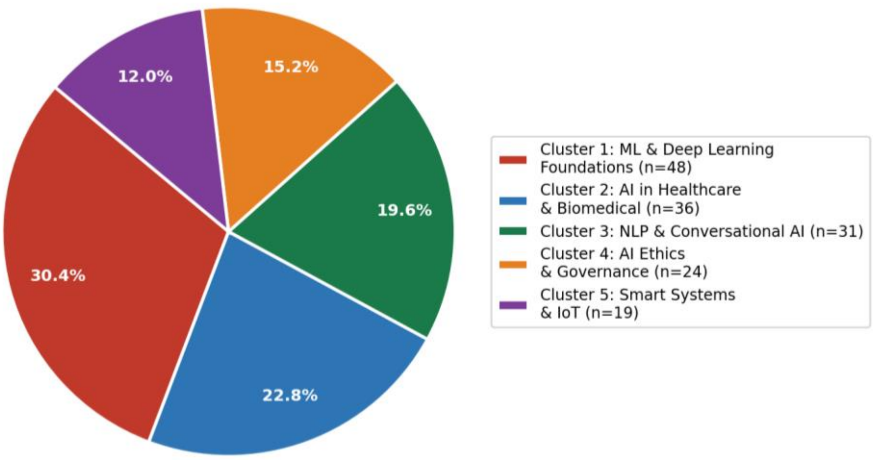

Figure 6. Co-citation Cluster Distribution (n = 158 documents, 5 major clusters)

Strategic Thematic Map

Figure 7 presents the strategic thematic map (Callon's framework) positioning AI research themes across four quadrants based on centrality (relevance to the field) and density (internal development). Machine Learning, Deep Learning, NLP, and Healthcare AI occupy the Motor Themes quadrant, while Generative AI and AI Governance are classified as Emerging Themes.

Figure 7. Strategic Thematic Map of AI Research Using Callon's Framework (Bibliometrix, R)

The findings confirm that machine learning and deep learning remain the backbone of contemporary *Artificial Intelligence* (AI) research. The substantial growth in AI-related publications during 2023–2024 can largely be attributed to the mainstream adoption of large language models (LLMs), which have significantly influenced both academic research agendas and industrial applications. The growing prominence of Explainable AI (XAI) also reflects increasing regulatory and societal demands for transparency and accountability, particularly in high-stakes domains such as healthcare and criminal justice. Geographically and institutionally, the dominance of the United States and China reflects broader global dynamics in AI development, while the relatively limited representation of developing countries, particularly in Africa and Southeast Asia, highlights persistent inequalities in global AI research capacity. This imbalance raises concerns regarding the contextual transferability of AI solutions developed primarily in high-income countries to low-resource settings.

In terms of emerging research clusters and knowledge gaps, AI ethics and governance have become recognized areas of research; however, their relatively low publication volume (n = 24) compared with technical research clusters suggests that the ethical and societal dimensions of AI remain comparatively underexplored. Federated learning and multimodal AI represent promising niche areas with considerable research potential. Key knowledge gaps include the application of AI in resource-limited settings, longitudinal studies examining AI outcomes over time, cross-cultural research on AI acceptance, and empirical evaluation of AI governance frameworks. These findings have important implications for both research and practice. Researchers should expand AI studies beyond technically dominated approaches to incorporate greater attention to sociotechnical, ethical, and longitudinal dimensions. For practitioners and policymakers, the findings emphasize the importance of context-specific AI adoption strategies, robust governance frameworks, and investment in AI literacy programs, particularly in developing countries.

Conclusions

This study presents a comprehensive Systematic Literature Review and bibliometric analysis of 183 peer-reviewed articles on *Artificial Intelligence* published in Scopus-indexed journals between January 2022 and March 2026. By integrating PRISMA 2020 guidelines with VOSviewer and Bibliometrix, this review provides a methodologically rigorous synthesis of the AI research landscape. The findings demonstrate that AI research is growing at an unprecedented CAGR of ~28.4%, with the United States, China, and the United Kingdom as dominant contributors. Machine learning, deep learning, and NLP are established motor themes, while generative AI, AI ethics, and AI governance are rapidly emerging. Five major thematic clusters were identified through co-citation analysis. Significant knowledge gaps remain regarding AI in developing-country contexts, longitudinal outcome studies, and empirical governance evaluations. The seven-point research agenda proposed in this review is intended to guide future scholarship toward these underexplored yet critically important areas.

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