

Mapping the Global Knowledge Structure of Artificial Intelligence (AI) in Risk Management: A Bibliometric Analysis

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Abstract

This study maps the global knowledge structure of artificial intelligence (AI) in risk management using bibliometric analysis. Bibliographic data were retrieved from the Scopus database on 17 July 2026 using a structured search strategy combining AI-related and risk-management-related terms. A total of 2,353 records were retrieved, of which 2,195 publications from 2017–2026 were considered for the main analysis. The study examines publication growth, document types, productive authors, sources, countries, institutions, citation patterns, and research themes. The findings reveal a substantial increase in scholarly output, with publications rising from 16 in 2017 to 800 in 2025 and a CAGR of 54.48% for the completed period. Articles constituted the largest document type (44.37%). India was the leading contributing country, while Amity University was the most productive institution. The findings demonstrate the rapid expansion, interdisciplinary character, and geographically diverse development of AI research in risk management.

Keywords: Artificial Intelligence; Risk Management; Risk Analysis; Bibliometric Analysis; Research Trends.

1. Introduction

Artificial intelligence (AI) has evolved from a specialized area of computer science into a pervasive technological capability influencing decision-making, business processes, public services, healthcare, finance, manufacturing, cybersecurity, and other domains. The rapid development of machine learning, deep learning, natural language processing, and data-driven analytical techniques has substantially expanded the capacity of organizations to process complex information, identify patterns, predict outcomes, and support decisions under uncertainty (Jordan & Mitchell, 2015). The increasing availability of large datasets, computational resources, and sophisticated learning algorithms has accelerated the adoption of AI across scientific, industrial, and organizational settings. Consequently, AI is increasingly being considered not only as a tool for automation and prediction but also as an important component of contemporary decision-support and risk-management systems.

Risk management traditionally involves systematic identification, assessment, monitoring, and mitigation of uncertainties that may adversely affect organizational objectives. The integration of AI and machine learning has introduced new possibilities for improving risk identification, prediction, classification, anomaly detection, fraud detection, credit assessment, operational risk monitoring, and decision support. In financial services, for example, AI and machine learning have been applied to credit risk, market risk, operational risk, fraud detection, and regulatory technology (Aziz & Dowling, 2019). Recent bibliometric research in the financial services domain has likewise demonstrated the growing intersection of AI, machine learning, risk management, fintech, anti-money-laundering, and actuarial research (Pattnaik et al., 2024). However, the use of AI for risk management also creates a distinctive set of technological, data-related, organizational, ethical, and regulatory challenges. AI systems may be affected by biased or incomplete training data, dataset shifts, model misspecification, prediction uncertainty, adversarial attacks, and limitations associated with deployment environments (Zhang et al., 2022). These risks are particularly significant when AI systems are used in high-impact contexts in which inaccurate or inappropriate predictions can have substantial consequences. Amodei et

al. (2016) highlighted problems such as unintended behavior, reward hacking, inadequate supervision, and distributional shift as important dimensions of AI safety. More broadly, the increasing use of algorithmic systems for consequential decisions has raised concerns regarding fairness, accountability, transparency, privacy, and discrimination (Barocas & Selbst, 2016; Mittelstadt et al., 2016).

The interpretability and explainability of AI systems represent another important dimension of AI-related risk management. Many contemporary machine learning models can produce highly accurate predictions while providing limited insight into how particular decisions are generated. This creates challenges for organizations that need to validate, audit, explain, and govern AI-supported decisions. Ribeiro et al. (2016) emphasized the importance of interpretable explanations for understanding machine-learning predictions, while Doshi-Velez and Kim (2017) argued for a more rigorous scientific basis for evaluating interpretability. Rudin (2019) further highlighted the importance of inherently interpretable models in high-stakes decision-making. These concerns make transparency and explainability important components of risk identification and mitigation rather than merely technical characteristics of AI systems.

Alongside technical risks, AI governance has emerged as an important research area. The growing deployment of AI has stimulated the development of principles, guidelines, organizational controls, and regulatory approaches intended to promote responsible and accountable AI. Jobin et al. (2019), in their analysis of global AI ethics guidelines, identified recurring principles including transparency, fairness, non-maleficence, responsibility, and privacy, while also demonstrating substantial differences in how these principles are interpreted and operationalized. Similarly, Wirtz et al. (2022) proposed a risk- and guideline-based framework that connects technological, data, economic, social, ethical, and legal risks with governance mechanisms. Recent systematic reviews indicate that AI governance research remains diverse and fragmented, with continuing challenges in translating high-level principles into operational organizational practices (Batool et al., 2025; Papagiannidis et al., 2025).

The growing complexity of AI-related risks has therefore encouraged a shift from viewing risk as a purely technical problem toward more integrated approaches encompassing human, organizational, societal, and regulatory dimensions. Human-centered AI perspectives emphasize the importance of designing AI systems that are reliable, safe, trustworthy, and compatible with meaningful human control (Shneiderman, 2020). Similarly, research on human trust in AI indicates that successful organizational adoption depends partly on how users perceive and understand AI capabilities and limitations (Glikson & Woolley, 2020). These perspectives reinforce the importance of considering AI risk management across the entire AI lifecycle, including design, development, validation, deployment, monitoring, and post-deployment evaluation.

Despite the rapid expansion of research on AI and risk management, the knowledge base remains dispersed across multiple disciplines and application contexts. Existing studies have examined AI risks, governance, ethics, explainability, financial risk, cybersecurity, healthcare, operations, and organizational decision-making, but these streams are often investigated independently. Recent research on risk-aware AI/ML systems specifically calls for a more systematic understanding of the heterogeneous sources of risk and the development of integrated approaches to risk analysis and management (Zhang et al., 2022). Similarly, recent AI governance reviews identify fragmentation in the literature and emphasize the need to understand relationships among governance principles, organizational practices, regulatory requirements, and AI lifecycle management (Batool et al., 2025; Papagiannidis et al., 2025).

In this context, bibliometric analysis provides a systematic means of examining the intellectual, conceptual, and social structure of a rapidly expanding research domain. Bibliometric methods enable researchers to quantitatively examine publication productivity, citation patterns, influential authors, sources, institutions, countries, collaboration networks, and emerging research themes (Zupic & Čater, 2015; Donthu et al., 2021). Science-mapping techniques can additionally reveal relationships among research topics and identify intellectual and thematic clusters within a literature that may be difficult to understand through conventional narrative reviews alone. Tools such as VOSviewer and bibliometrix facilitate the visualization and analysis of

bibliographic networks, including co-authorship, co-occurrence, bibliographic coupling, and co-citation structures (van Eck & Waltman, 2010; Aria & Cuccurullo, 2017).

Although bibliometric studies have examined AI applications in specific areas such as financial services and financial risk management, a broader mapping of the global knowledge structure of AI in risk management remains valuable. A recent bibliometric review of AI in financial risk management, for instance, focused specifically on financial risk and analyzed 791 Scopus-indexed publications from 1987–2025 (Hafiz et al., 2026). The broader literature, however, encompasses risks extending beyond finance, including data and model risks, operational risks, ethical risks, cybersecurity risks, governance risks, social risks, and regulatory risks.

Therefore, the present study, titled *“Mapping the Global Knowledge Structure of Artificial Intelligence in Risk Management: A Bibliometric Analysis,”* aims to provide a comprehensive quantitative and science-mapping assessment of the development and structure of this interdisciplinary research field. The study examines the temporal evolution of publications, productive authors, leading sources, countries and institutions, citation patterns, collaboration structures, and thematic developments. By integrating performance analysis with science-mapping approaches, the study seeks to identify the major contributors, intellectual foundations, dominant research themes, emerging areas, and potential research gaps within the AI–risk management knowledge domain. The findings are expected to provide researchers, academic institutions, practitioners, and policymakers with a structured understanding of how the field has evolved and where future research opportunities are emerging.

2. Objectives

- To examine the growth of publications on artificial intelligence in risk management.
- To identify the most productive authors, sources, countries, and institutions in the field.
- To identify the major research themes and emerging trends in artificial intelligence and risk management.

3. Methodology

The study employed a bibliometric research design to examine the global research landscape of artificial intelligence in risk management. Bibliographic data were retrieved from the Scopus database on 17 July 2026 using the following search string:

“TITLE-ABS-KEY(("artificial intelligence" OR AI OR "machine learning") AND ("financial risk" OR "credit risk" OR "market risk" OR "investment risk" OR "risk management"))”.

The TITLE-ABS-KEY field searches the title, abstract, and keywords of Scopus-indexed documents. The search retrieved 2,353 documents, which were exported in CSV format for analysis. Of these, 2,195 documents were published during 2017–2026 and were considered for the main analysis. The study examined annual publication growth, productive authors, sources, countries, institutions, citation patterns, and research themes. Annual growth rates and percentage contributions were calculated using standard bibliometric measures. Keyword analysis was used to identify major research themes and emerging trends. The study provides a quantitative overview of the development and knowledge structure of AI research in risk management.

4. Data Analysis and Interpretation

Table 1. Annual Growth and Distribution of Publications

Year	Publications	Absolute Increase	Annual Growth (%)	Share of Total (%)	Cumulative Publications
2017	16	–	–	0.73	16
2018	30	14	87.50	1.37	46
2019	44	14	46.67	2.00	90
2020	65	21	47.73	2.96	155

2021	97	32	49.23	4.42	252
2022	133	36	37.11	6.06	385
2023	181	48	36.09	8.25	566
2024	371	190	104.97	16.90	937
2025	800	429	115.63	36.45	1,737
2026	458	-342	-42.75	20.87	2,195
Total	2,195	—	—	100.00	—

Note: *partial-year publication count

The Scopus database yielded 2,353 records in total, of which 2,195 publications were published during the period 2017–2026. The annual publication output demonstrates a substantial expansion of research on artificial intelligence and risk management. Publications increased progressively from 16 in 2017 to 800 in 2025. The number of publications increased from 16 in 2017 to 30 in 2018, representing an annual growth of 87.50%, followed by 46.67% growth in 2019 and 47.73% in 2020. The publication output continued to increase during 2021–2023, reaching 97, 133 and 181 publications, respectively. A particularly pronounced increase occurred in 2024, when the publication output reached 371 publications, representing a 104.97% increase compared with 2023. The highest completed annual publication output was recorded in 2025, with 800 publications, representing a 115.63% increase over 2024.

The Scopus data contains 458 publications for 2026. Since the dataset was retrieved on 17 July 2026, the 2026 figure represents a partial-year publication count and therefore should not be directly compared with the completed annual counts of previous years. Consequently, the apparent decrease from 800 publications in 2025 to 458 publications in 2026 should not be interpreted as a decline in research productivity. The publication output increased substantially during the study period. From 2017 to 2025, the number of publications increased from 16 to 800, an overall increase of 4,900%. The compound annual growth rate (CAGR) for the completed period was approximately 54.48%, indicating rapid expansion of scholarly research at the intersection of artificial intelligence and risk management.

Table 2. Descriptive Statistics of Publications

Statistical Measure	Value
Study period	2017–2026
Total publications	2,195
Number of years	10
Mean publications per year	219.50
Median publications per year	115.00
Minimum publications	16 (2017)
Maximum publications	800 (2025)
Range	784
CAGR, 2017–2026	45.16%
Overall increase, 2017–2026	2,762.50%

Formulas Used

Annual Growth Rate:

$$\text{Annual Growth Rate (\%)} = [(Pt - Pt-1) / Pt-1] \times 100$$

Where:

Pt = Publications in the current year

Pt-1 = Publications in the previous year

Absolute Increase:

$$\text{Absolute Increase} = Pt - Pt-1$$

Percentage Share of Total Publications:

$$\text{Percentage Share (\%)} = (Pt / P_{total}) \times 100$$

Where:

Pt = Publications in a particular year

Ptotal = Total publications during the study period

CAGR:

$$\text{CAGR (\%)} = [(Pf / Pi)^{(1/n)} - 1] \times 100$$

Where:

Pf = Publications in the final year

Pi = Publications in the initial year

n = Number of years/intervals between the initial and final year.

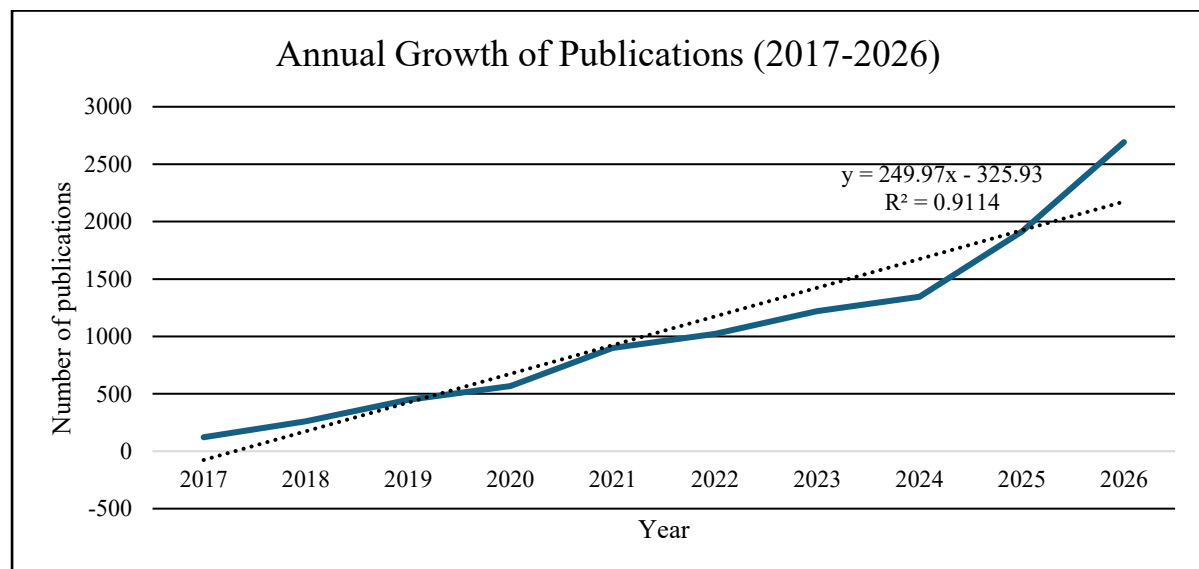


Figure 1. Annual Growth of Publications

Table 3. Distribution of Publications by Document Type

Document Type	Publications	Percentage (%)
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Article	974	44.37
Book chapter	580	26.42
Conference paper	358	16.31
Book	176	8.02
Review	65	2.96
Conference review	27	1.23
Editorial	5	0.23
Note	5	0.23
Erratum	2	0.09
Retracted	2	0.09
Short survey	1	0.05
Total	2,195	100.00

Table 3 presents the distribution of the 2,195 publications by document type in the field of artificial intelligence and risk management during 2017–2026. Articles constituted the largest document type, with 974 publications (44.37%), indicating that peer-reviewed journal articles were the primary medium for disseminating research in this field. Book chapters ranked second, accounting for 580 publications (26.42%), followed by conference papers with 358 publications (16.31%). Books contributed 176 publications (8.02%), while reviews accounted for 65 publications (2.96%). Other document types represented only a small proportion of the total output. Conference reviews accounted for 27 publications (1.23%), whereas editorials and notes contributed 5 publications each (0.23%). Errata and retracted documents accounted for 2 publications each (0.09%), and short surveys represented only 1 publication (0.05%).

Overall, articles, book chapters, and conference papers together accounted for 1,912 publications, representing 87.10% of the total research output. This indicates that scholarly communication in AI and risk management is predominantly conducted through research articles, book chapters, and conference proceedings. The relatively high proportion of book chapters and conference papers also reflects the interdisciplinary and rapidly developing nature of the field, where emerging research is disseminated through diverse academic publication channels. The presence of retracted documents, although very limited (0.09%), indicates the importance of maintaining research integrity and quality control in the literature.

Table 4. Top 10 Most Productive Countries

Rank	Country	No. of Publications	Percentage (%)	Cumulative Share (%)
1	India	481	21.91	21.91
2	United States	309	14.08	35.99
3	China	285	12.98	48.97
4	United Kingdom	154	7.02	55.99
5	Italy	80	3.64	59.64
6	Germany	80	3.64	63.28
7	Australia	71	3.23	66.51

8	France	68	3.10	69.61
9	Turkey	62	2.82	72.44
10	Malaysia	61	2.78	75.22

Table 4 presents the ten most productive countries contributing to research on artificial intelligence in risk management during 2017–2026. India emerged as the leading contributor with 481 publications, representing 21.91% of the 2,195 publications included in the study. The United States ranked second with 309 publications (14.08%), followed by China with 285 publications (12.98%). The United Kingdom occupied the fourth position with 154 publications, accounting for 7.02% of the total research output. Italy and Germany contributed 80 publications each, representing 3.64% each, while Australia produced 71 publications (3.23%). France ranked eighth with 68 publications (3.10%), followed by Turkey with 62 publications (2.82%) and Malaysia with 61 publications (2.78%).

The findings demonstrate a geographically diverse research landscape, with substantial contributions originating from Asia, North America, Europe, and Australia. India, the United States, China, and the United Kingdom constitute the most prominent contributors to the literature. The strong representation of countries from different geographical regions indicates the global relevance of artificial intelligence applications in risk management and the growing international research interest in this domain. It should be noted that publications involving international collaboration may be attributed to more than one country based on the affiliations of the contributing authors. Consequently, country-level publication percentages are not mutually exclusive and should be interpreted as the proportion of the dataset in which each country is represented.

Table 5. Top 10 Most Productive Institutions

Rank	Institution	No. of Publications	Percentage (%)	Cumulative Share (%)
1	Amity University	34	1.55	1.55
2	Lovely Professional University	25	1.14	2.69
3	Chandigarh University	23	1.05	3.74
4	University of Johannesburg	23	1.05	4.78
5	Christ University	21	0.96	5.74
6	Chitkara University	14	0.64	6.38
7	The Hong Kong Polytechnic University	12	0.55	6.92
8	SRM Institute of Science and Technology	12	0.55	7.47
9	University of Bahrain	10	0.46	7.93
10	University of Delhi	9	0.41	8.34

Table 5 presents the ten most productive institutions contributing to research on artificial intelligence in risk management during 2017–2026. Amity University emerged as the most productive institution, contributing to 34 publications, representing 1.55% of the total 2,195 publications. Lovely Professional University ranked second with 25 publications (1.14%), followed by Chandigarh University and the University of Johannesburg, each contributing 23 publications (1.05%). Christ University occupied the fifth position with 21 publications, accounting for 0.96% of the total research output. Chitkara University contributed 14 publications (0.64%),

while The Hong Kong Polytechnic University and SRM Institute of Science and Technology each contributed 12 publications (0.55%). The University of Bahrain ranked ninth with 10 publications (0.46%), followed by the University of Delhi with 9 publications (0.41%).

The institutional distribution reveals contributions from universities located across several countries and regions. Indian institutions are particularly prominent among the most productive organizations, with Amity University, Lovely Professional University, Chandigarh University, Christ University, Chitkara University, SRM Institute of Science and Technology, and the University of Delhi appearing among the top ten. At the same time, the presence of the University of Johannesburg, The Hong Kong Polytechnic University, and the University of Bahrain demonstrates the international institutional participation in this research domain. The relatively low individual percentage shares of even the leading institutions suggest that the literature on artificial intelligence in risk management is institutionally dispersed rather than concentrated within a small number of organizations. This broad institutional participation further indicates the multidisciplinary and internationally distributed nature of research in the field.

Table 6. Top 10 Most Productive Authors

Rank	Author	No. of Publications	Percentage (%)	Cumulative Share (%)
1	Al Janabi, Mazin A.M.	9	0.41	0.41
2	Khang, Alex	7	0.32	0.73
3	Irfan, Mohammad	7	0.32	1.05
4	Vashishth, Tarun Kumar	5	0.23	1.28
5	Sharma, Vikas	5	0.23	1.50
6	Grima, Simon	5	0.23	1.73
7	Balusamy, Balamurugan	5	0.23	1.96
8	Baryannis, George	5	0.23	2.19
9	Singh, Partap	4	0.18	2.37
10	Fantazzini, Dean	4	0.18	2.55
Total		56	2.55	2.55

Table 6 presents the most productive authors contributing to research on artificial intelligence in risk management during 2017–2026. The analysis is based on 2,195 publications retrieved from Scopus. The results indicate that the authorship landscape is relatively dispersed, with no single author accounting for a substantial proportion of the total publication output. Al Janabi, Mazin A.M. emerged as the most productive author, contributing 9 publications, representing 0.41% of the total publication output. Khang, Alex and Irfan, Mohammad followed with 7 publications each, corresponding to 0.32% each. Five publications were contributed by each of Vashishth, Tarun Kumar; Sharma, Vikas; Grima, Simon; Balusamy, Balamurugan; and Baryannis, George, with each author accounting for 0.23% of the total publications. Singh, Partap and Fantazzini, Dean contributed 4 publications each, representing 0.18% each. Collectively, the ten most productive authors contributed 56 publications, accounting for 2.55% of the 2,195 publications in the dataset.

The relatively small share of publications attributed to the top ten authors indicates that research productivity is distributed across a large number of contributors rather than being concentrated among a small group of highly productive authors. This pattern may reflect the multidisciplinary and collaborative nature of research at the intersection of artificial intelligence and risk management, where researchers from different disciplines and

geographical regions contribute to the literature. The results further demonstrate that the field is not dominated by a single prolific author. The difference between the most productive author, with 9 publications, and the authors ranked second and third, with 7 publications each, is relatively small. This suggests a broad distribution of research contributions among active researchers within the field.

Table 7. Top 10 Most Productive Sources in Artificial Intelligence in Risk Management Research.

Rank	Source Title	No. of Publications	Percentage (%)	Cumulative Share (%)
1	Journal of Risk and Financial Management	82	3.74	3.74
2	Risks	56	2.55	6.29
3	Technological Forecasting and Social Change	24	1.09	7.38
4	Financial Innovation	18	0.82	8.20
5	Advances in Transdisciplinary Engineering	18	0.82	9.02
6	Springer Proceedings in Business and Economics	18	0.82	9.84
7	Journal of Cleaner Production	17	0.77	10.62
8	International Journal of Production Research	16	0.73	11.34
9	IEEE Transactions on Engineering Management	16	0.73	12.07
10	Lecture Notes in Business Information Processing	15	0.68	12.76
Total	Top 10 sources	280	12.76	12.76

Table 7 presents the ten most productive sources publishing research related to artificial intelligence in risk management during 2017–2026. The analysis is based on 2,195 publications retrieved from Scopus. The results indicate that the literature is distributed across a diverse range of journals, book series, and conference-related sources. The Journal of Risk and Financial Management emerged as the most productive source, accounting for 82 publications, equivalent to 3.74% of the total publications. Risks ranked second with 56 publications (2.55%), followed by Technological Forecasting and Social Change with 24 publications (1.09%). Financial Innovation, Advances in Transdisciplinary Engineering, and Springer Proceedings in Business and Economics each contributed 18 publications, representing 0.82% of the total output. Journal of Cleaner Production ranked seventh with 17 publications (0.77%), while International Journal of Production Research and IEEE Transactions on Engineering Management contributed 16 publications each (0.73%). Lecture Notes in Business Information Processing occupied the tenth position with 15 publications (0.68%).

Collectively, the top ten sources accounted for 280 publications, representing 12.76% of the total 2,195 publications. This indicates that the research literature is not concentrated in a small number of publication venues; rather, it is dispersed across multiple sources covering risk management, finance, technology forecasting, operations, sustainability, engineering, and information systems. The presence of sources from different disciplinary areas also reflects the interdisciplinary nature of artificial intelligence and risk

management research. The leading sources span financial risk, technological innovation, sustainability, production and operations, engineering management, and information processing, suggesting that AI-based risk management is being investigated across multiple academic domains.

5. Conclusion

This bibliometric study provides an overview of the global research landscape of artificial intelligence in risk management based on Scopus-indexed publications. The analysis demonstrates a substantial and rapid expansion of research in this field, with publication output increasing from 16 publications in 2017 to 800 publications in 2025. The CAGR of 54.48% for the completed period further indicates the rapid growth of scholarly interest in AI and risk management. Articles represented the largest document type, accounting for 44.37% of the publications, followed by book chapters and conference papers. The analysis of productive contributors shows that the research field is widely distributed among authors and institutions. India emerged as the leading contributing country, while Amity University was the most productive institution. The leading sources also represent diverse areas including risk management, finance, technology, engineering, sustainability, and information systems, demonstrating the interdisciplinary nature of the field.

Overall, the findings indicate that AI in risk management is an expanding and multidisciplinary research domain. Future research may focus on strengthening explainability, responsible AI, governance, data and model risks, cybersecurity, and the practical implementation of AI-based risk-management systems. Since the 2026 data were retrieved on 17 July 2026, the 2026 publication count represents a partial year and should therefore be interpreted cautiously.

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