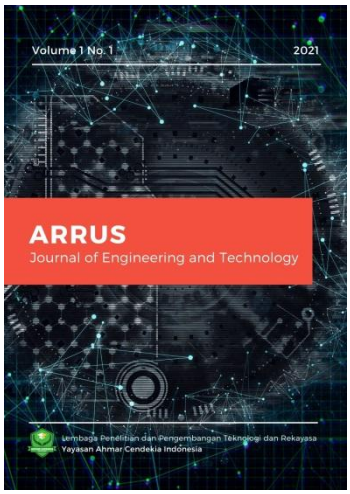
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RESEARCH ARTICLE

Global Publications on Financial Technology and Artificial Intelligence: A Bibliometric Analysis

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Abstract: This study presents a comprehensive bibliometric analysis and science mapping of global research on the integration of Financial Technology (Fintech) and Artificial Intelligence (AI) / Machine Learning (ML) within the Banking, Financial Services, and Insurance (BFSI) sector from 2015 to 2025. Utilizing 312 Scopus-indexed documents extracted via the PRISMA 2020 protocol and analyzed using VOSviewer, the findings reveal an exponential growth in publications, with over 75% published between 2023 and 2025. The intellectual structure comprises four main thematic clusters: (1) AI in digital banking and financial services transformation, (2) deep learning for fraud detection, cybersecurity, and risk management, (3) machine learning and explainability (XAI/SHAP) for credit risk and P2P lending, and (4) fintech adoption, digital payments, and blockchain. Furthermore, the analysis highlights a shifting trend from classical risk modeling toward cybersecurity, regulatory compliance (RegTech), and financial inclusion. Finally, this paper outlines key research gaps and future directions, including the broader application of Generative AI/LLMs in risk assessment, enhanced model explainability, and stronger alignment between technical AI models and regulatory frameworks.

Keywords: Bibliometric analysis, Fintech, Artificial intelligence, Machine learning, VOSviewer

1. Introduction

The massive development of the digital era drives a profound structural transformation across global industry sectors, with the banking, financial services, and insurance (BFSI) industry at the forefront of adopting cutting-edge financial technology (Boustani, 2020). This transformation focuses not only on digitalizing traditional services but also on integrating cognitive computing systems to improve operational efficiency and macroeconomic resilience (Vives, 2019). In the context of the modern financial ecosystem, the very large volume of transaction data demands advanced analytical capabilities that go beyond conventional methods (Ghazali et al., 2022). Therefore, the adoption of intelligent technology becomes a strategic foundation for financial institutions to remain competitive amid global market dynamics that are increasingly complex, interconnected, and fully digitized (Vijai, 2019).

In response to these challenges, the adoption of Artificial Intelligence (AI) and Machine Learning (ML) is a main pillar of contemporary financial service innovation and the Banking 4.0 era (Kumar et al., 2022). This technology enables financial institutions to automate

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complex business processes, accelerate credit risk analysis, and optimize investment portfolio allocation in real time (Leo et al., 2019). Through predictive algorithms, financial institutions identify customer behavior patterns more accurately in order to deliver relevant product personalization (Goodell et al., 2021). This comparative advantage makes the integration of AI and ML a crucial instrument in redefining the operational standards and service architecture of the modern financial services industry (Fernandez-Vazquez et al., 2023).

Despite its enormous transformative potential, implementing AI and ML in the BFSI sector also raises various theoretical and empirical complexities that require in-depth study (Belanche et al., 2019). The development of the literature shows that scientific publications on the adoption of these technologies grow exponentially as the integration of finance and technology (fintech) increases (Milian et al., 2019). Even so, a comprehensive mapping of research trends, global collaboration, and the thematic roadmap of AI and ML applications in the financial sector still requires systematic synthesis. Several earlier studies, such as the one developed by Kumar et al. (2022) highlight the shift of the banking landscape toward the era of artificial intelligence, while Mukthar et al. (2025) emphasize the importance of bibliometric mapping for understanding the evolution of AI and fintech research globally.

To strengthen this understanding, bibliometric studies play an important role in objectively mapping the intellectual structure and scientific evolution of a research field (Donthu et al., 2021). Through bibliometric analysis and science network mapping, researchers can comprehensively identify the most influential documents, the main thematic clusters, and the collaboration networks among researchers worldwide (Aria & Cuccurullo, 2017). This approach enables the identification of current research trends that are the main focus of the international academic community in examining the strategic impact of AI and ML on the financial industry (Zetzsche et al., 2020). Thus, bibliometric analysis functions as a theoretical compass for organizing a broad and fragmented research landscape into a more structured and measurable knowledge framework (Kraus et al., 2020).

Various earlier studies attempt to document the evolution of financial technology, but mapping that specifically integrates the analysis of global publications on AI and ML in the BFSI sector still leaves a gap (research gap). As highlighted in the main literature review by Pattnaik et al. (2024), most existing literature reviews still provide fragmented insights, so a comprehensive PRISMA-based analysis is required to capture the shifts in research focus over time. In addition, recent studies often under-explore comprehensive long-term implications, such as ethics, data privacy risks, regulatory challenges (RegTech), and overall socioeconomic impacts (Arner et al., 2020; Kumar et al., 2022; Mukthar et al., 2025). These studies affirm the need for continuous evaluation of the direction of literature development so that practitioners and academics can seize opportunities and navigate future challenges.

Based on this background and the identified literature gap, this study aims to conduct a comprehensive bibliometric search and mapping of scientific publications that examine the application of artificial intelligence and machine learning in the banking, financial services, and insurance sector. This study is expected to make a significant contribution, both theoretically by enriching the financial technology management literature and practically as a strategic guide for decision-makers in the BFSI industry (Ghazali et al., 2022). Through a systematic research map, this study not only summarizes existing academic achievements but also opens room for exploring further topics that earlier researchers rarely explore related to governance, risk mitigation, and the sustainability of AI-based financial ecosystems (Ravanfar et al., 2023).

To bridge this research gap, this bibliometric study is explicitly designed to answer three (3) main Research Questions (RQ) as follows:

(1). RQ1: How do the quantitative publication dynamics, author productivity, institutional contributions, and patterns of cross-country collaboration networks develop in the literature on the integration of Fintech and Artificial Intelligence over the 2015–2025 period?

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(2). RQ2: What are the thematic structure and science mapping of the main topics, along with the shifting keyword trends (overlay visualization), in the field of Fintech and AI research?

(3). RQ3: What research gaps and future research directions are identified for developing the integration of AI and fintech?

Based on the formulation of the research questions above, the objective of this study is to map the performance of scientific publications, to map the taxonomy of the thematic structure visually using VOSviewer, and to formulate a matrix of future research agenda recommendations for practitioners, academics, and regulators in building safe, transparent, and sustainable AI and fintech governance.

2. Research Method and Materials

2.1. Research Design and Approach

This study uses a descriptive quantitative approach with bibliometric analysis and science mapping methods. Bibliometric analysis is used to evaluate publication trends, author productivity, institutions, countries, and their impact through citation analysis in the field of integrating Financial Technology (Fintech) and Artificial Intelligence (AI). Meanwhile, science mapping is applied to identify the thematic structure, the evolutionary dynamics of keywords, and future research gaps.

2.2. Data Search Strategy and Extraction Flow (PRISMA 2020)

Documentary data are extracted from the Scopus database on 4 November 2026. Data collection follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) protocol. Unlike generic searches that scan abstracts and keywords, the search strategy in this study focuses specifically on the article title field (TITLE) to ensure high precision and relevance to the Fintech and AI theme. The inclusion and exclusion criteria are as follows:

(1). **Time Range:** Limited to publications from 2015 to 2025 to capture the research dynamics of the last decade.

(2). **Document Type:** Includes journal articles and conference proceedings papers to obtain comprehensive coverage of empirical research and the latest technological developments.

(3). **Language:** English-language documents.

(4). **Source Type:** Journals and conference proceeding series.

(5). **Scopus Search String:**

TITLE ((fintech OR "financial technolog*" OR "digital financ*" OR "digital banking" OR "online lending" OR "peer-to-peer lending" OR "robo-advis*" OR regtech OR "mobile payment*" OR "digital payment*" OR "open banking") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "natural language processing" OR "generative AI" OR "large language model*" OR chatbot* OR "explainable AI")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (SRCTYPE , "p") OR LIMIT-TO (SRCTYPE , "j")) AND PUBYEAR > 2014 AND PUBYEAR < 2026

The initial search yields n = 313 documents. After a duplicate check based on the Digital Object Identifier (DOI), 1 duplicate document is removed (n = 1). Thus, the final dataset analyzed totals 312 documents (172 journal articles and 140 conference papers) published by 249 sources, as shown in Figure 1.

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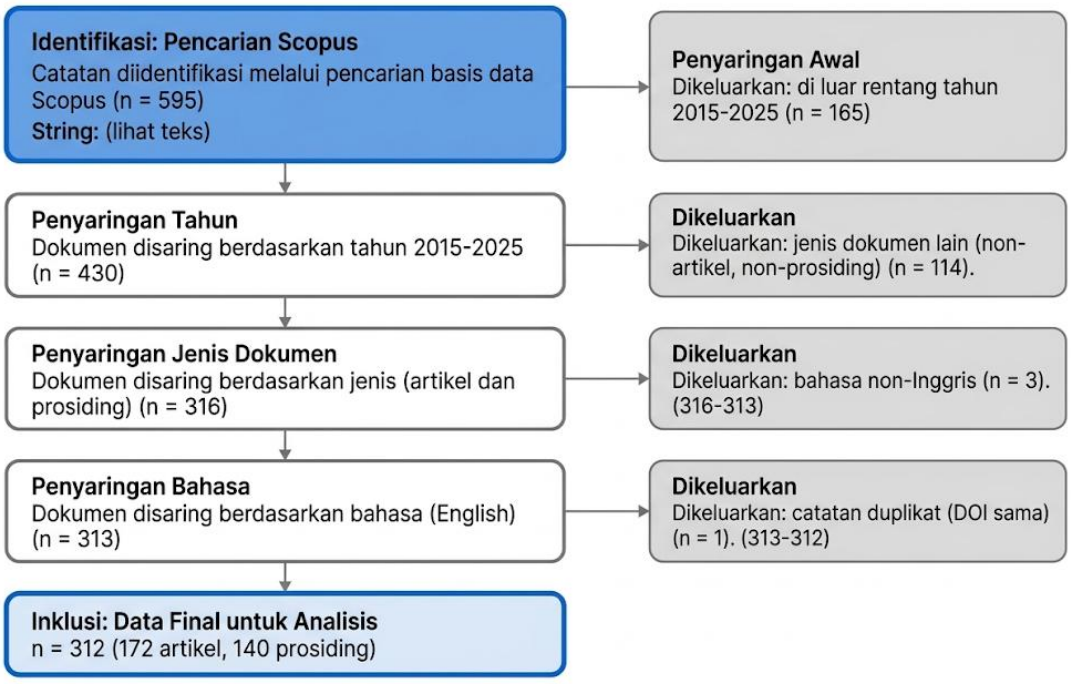


Figure 1. PRISMA Diagram

2.3. *Data Cleaning and Harmonization*

Before quantitative analysis and network visualization, comprehensive data cleaning is applied to ensure the validity of the results. The cleaning stages include:

(1). **Country Harmonization:** Country names are adjusted to the Scopus standard and affiliation names are corrected (for example, Russian Federation is changed to Russia, Viet Nam to Vietnam, and CityU Hong Kong, listed under 'China', is separately changed to Hong Kong). Following Scopus convention, Taiwan and Hong Kong are counted separately from China. Of the 77 countries identified, 5 documents have no country affiliation record.

(2). **Institution Harmonization:** From 800 unique affiliation strings, 39 merging rules and 28 manual corrections are applied. Units below the university level (such as faculties and research institutes) are merged into their parent university (for example, the variants Universitas Bina Nusantara and Binus University are unified as Bina Nusantara University). The cleaning reduces the number of unique institutions from 647 to 589.

(3). **Source Harmonization:** Conference series recorded separately by year/edition are merged (for example, AMCIS, ICTBIG, ICBATS, ICDSAAI, and IC3I), which reduces the number of sources from 254 to 249.

(4). **Author Harmonization:** Authors are identified using Scopus Author IDs to avoid conflating authors with the same name (author name disambiguation). Manual corrections are made (such as merging Ariza-Garzón, who has two separate IDs), while authors with exactly identical names such as Li, Xin and Ma, Chao remain separate because their institutional affiliations differ. The total number of extracted authors is 1,026 unique authors.

(5). **Keyword Thesaurus Standardization:** Of the 895 original author keywords, 18 generic search terms are removed. 51 spelling/abbreviation merges and 14 conceptual merges based on a thesaurus file are performed. This cleaning reduces the keyword entities to 813 unique keywords (72 keywords meet the occurrence threshold of ≥ 3).

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Table 1. Summary of Data Cleaning

Data Element	Problem Identified	Cleaning Action	Cleaning Result
Country	Different official Scopus names; truncated affiliations; no country	Name harmonization (e.g., Russian Fed. → Russia); Hong Kong & Taiwan treated separately	77 countries (5 documents without affiliation)
Institution	Spelling variants, abbreviations, local languages, units below the university level	39 merging rules + 28 manual corrections; faculties/institutes merged into parent university	647 → 589 unique institutions
Source	Conference series recorded separately by year/edition	5 conference series merged per series (AMCIS, ICTBIG, ICBATS, ICDSAAI, IC3I)	254 → 249 sources
Author	One person with 2 Scopus IDs; same name belonging to different people	Ariza-Garzón merged; Li, Xin & Ma, Chao separated based on ID & institution	1,027 → 1,026 unique authors
Keyword	Varied spelling/abbreviations; plural forms; search terms counted	18 search terms removed; 51 spelling merges + 14 conceptual merges	895 → 813 unique keywords (72 keywords ≥ 3 occurrences)

2.4. *Analysis Techniques and Science Mapping*

Data analysis uses two main approaches:

(1). **Quantitative Descriptive Analysis:** Calculates the main research performance metrics, including annual publication volume growth (Total Publications/TP), citation accumulation (Total Citations/TC as of 4 November 2026), author productivity, the most productive institutions, and the Collaboration Index (CI), which is calculated as the total number of authors of multi-authored documents divided by the number of multi-authored documents.

(2). **Science Mapping (Co-occurrence Analysis):** Visualizes the thematic structure and network trends using VOSviewer software. The mapping parameters are set with the co-occurrence method on author keywords, the full counting technique, and association strength normalization. The minimum occurrence threshold is set at 3.

Visual mapping is divided into two main forms:

(1). **Network Visualization:** Identifies the main thematic clusters in the Fintech × AI domain.

(2). **Overlay Visualization:** Based on the average publication year, observes the shift in research trends from classical topics to emerging topics.

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3. Results and Discussion

3.1. *Performance Analysis Results*

The final data consist of 312 documents from 249 sources, written by 1,026 authors, with 895 unique author keywords, as presented in Table 2 below:

Table 2. Description of Results

Description	Results
Time span	2015–2025
Sources (journals and proceedings)	249
Documents	312
Journal articles	172
Conference papers	140
Average citations per document	26.78
Author keywords (DE)	895
Authors	1,026
Authors of single-authored documents	40
Authors of multi-authored documents	991
Average authors per document	3.41

Note: DE = Descriptors (author keywords)

3.1.1. *Publication and citation trends*

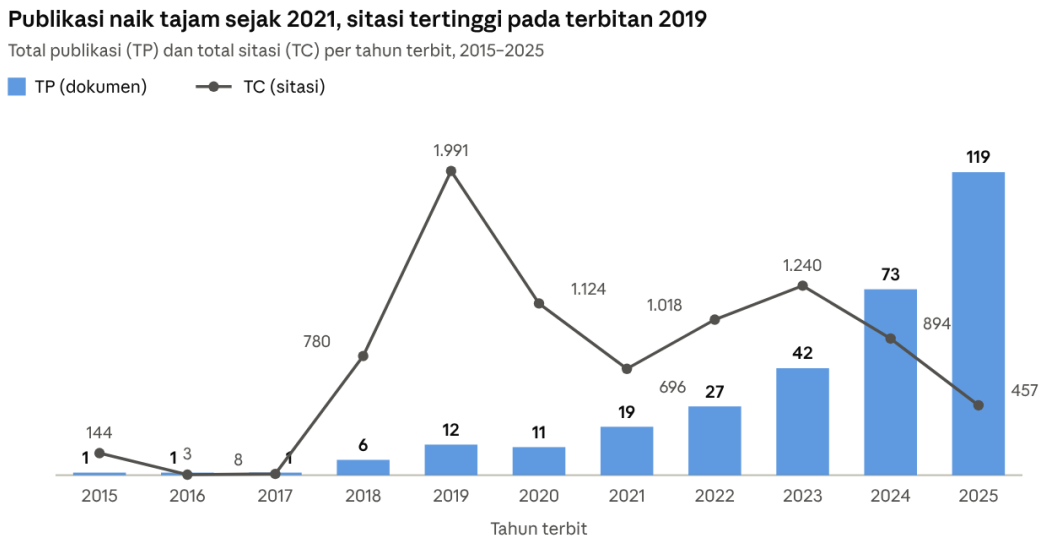


Figure 2. Publication and Citation Trends per Year

Based on Figure 2, publications in the field of fintech and AI increase from 1 document (2015) to 119 documents (2025), with 75% of documents published in 2023–2025. TC is calculated from the citations received by documents published in a given year, so the most recent years are naturally lower (citation lag); the peak occurs for 2019 publications (1,991 citations).

3.1.2. *Most productive and influential authors*

No author dominates: the highest productivity is only 3 documents (3 authors), and 33 other authors have 2 documents.

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Table 3. Ten Most Productive Authors

Author Name	Affiliation	Country	TP	TC	Rank
Abakah, E. J. A.	University of Ghana	Ghana	3	227	1
Huang, S. Y. B.	Ming Chuan University	Taiwan	3	121	2
Raju, V.	Mahsa University	Malaysia	3	36	3
Giudici, P.	University of Pavia	Italy	2	361	4
Ashta, A.	Université Bourgogne Franche-Comté	France	2	361	4
Tiwari, A. K.	Indian Institute of Management Bodh Gaya	India	2	219	5
Arroyo, J.	Universidad Complutense de Madrid	Spain	2	174	6
Ariza-Garzón, M. J.	Universidad Complutense de Madrid	Spain	2	174	6
Caparrini, A.	Management Solutions	Spain	2	174	6
Segovia-Vargas, M. J.	Universidad Complutense de Madrid	Spain	2	174	6

Note: TP = Total Publications; TC = Total Citations.

Table 4. Ten Most Influential Authors

Author Name	Affiliation	Country	TC	TP	Rank
Belanche, D.	University of Zaragoza	Spain	737	1	1
Casaló, L. V.	University of Zaragoza	Spain	737	1	1
Flavián, C.	University of Zaragoza	Spain	737	1	1
Kalinic, Z.	University of Kragujevac	Serbia	490	1	4
Liébana-Cabanillas, F.	University of Granada	Spain	490	1	4
Marinkovic, V.	University of Kragujevac	Serbia	490	1	4
Ramos de Luna, I.	University of Granada	Spain	490	1	4
Mhlanga, D.	University of Johannesburg	South Africa	489	1	8
Ashta, A.	Université Bourgogne Franche-Comté	France	361	2	9
Giudici, P.	University of Pavia	Italy	361	2	9

Note: TP = Total Publications; TC = Total Citations.

Based on Table 4, eight of the ten influential authors have only one document; their TC comes from the same two articles (Belanche et al., 2019; Liébana-Cabanillas et al., 2018). Only Ashta and Giudici appear in both tables. Equal TC values receive equal ranks.

3.1.3. Most influential documents

The ten most-cited documents receive 158–737 citations; seven of them are published in 2018–2020, before the surge in publications.

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Table 5. Ten Most-Cited Documents

No.	Authors	Title	Year	Source	Citations
1	Belanche et al.	Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers	2019	Industrial Management and Data Systems	737
2	Liébana-Cabanillas et al.	Predicting the determinants of mobile payment acceptance: A hybrid SEM-neural network approach	2018	Technological Forecasting and Social Change	490
3	Mhlanga	Industry 4.0 in finance: the impact of artificial intelligence (AI) on digital financial inclusion	2020	International Journal of Financial Studies	489
4	Ashta & Herrmann	Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance	2021	Strategic Change	322
5	Jagtiani & Lemieux	The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform	2019	Financial Management	314
6	Jakšič & Marinč	Relationship banking and information technology: the role of artificial intelligence and FinTech	2019	Risk Management	220
7	Bussmann et al.	Explainable AI in Fintech Risk Management	2020	Frontiers in Artificial Intelligence	203
8	Nguyen et al.	Big data, artificial intelligence and machine learning: A transformative symbiosis in favour of financial technology	2023	European Financial Management	178
9	Zhou et al.	Explainable artificial intelligence for digital finance and consumption upgrading	2023	Finance Research Letters	170
10	Giudici	Fintech Risk Management: A Research Challenge for Artificial Intelligence in Finance	2018	Frontiers in Artificial Intelligence	158

Note: citation counts are according to Scopus as of 4 November 2026. All documents in this table are journal articles.

3.1.4. Top sources and institutions

Publications are widely dispersed: 249 sources for 312 documents, and the top 16 sources contain only 61 documents (19.6%).

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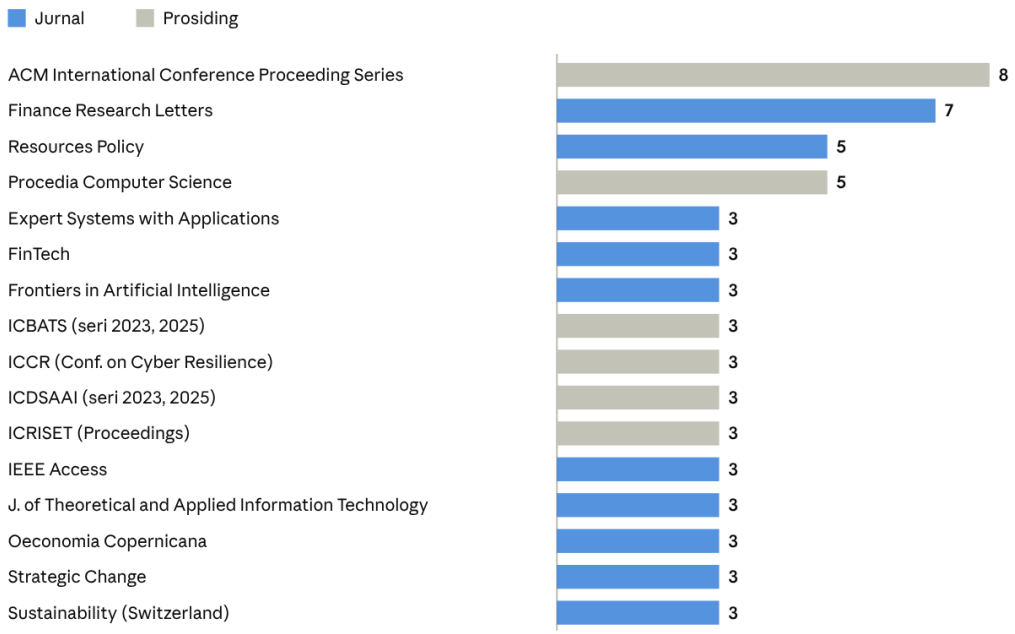


Figure 3. Top Sources by Total Publications, 2015–2025
Scopus export, 312 documents; the names of two proceedings are abbreviated

Twelve sources have the same count (3 documents), so the figure shows all sources with at least 3 documents, not just ten. Conferences are counted per series (different yearly editions are merged), so ICDSAAI and ICBATS now enter the list. Six of the 16 sources are proceedings.

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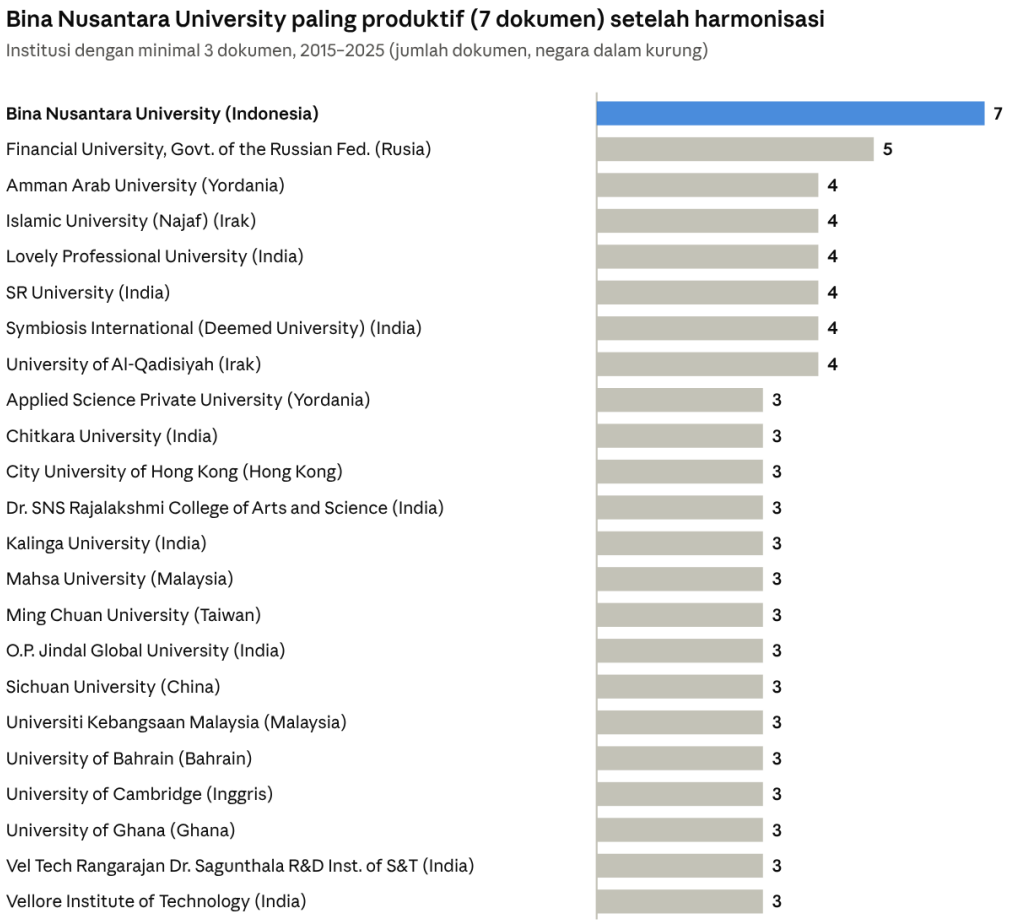


Figure 4. Top Institutions by Total Publications, 2015–2025
Scopus export, 312 documents; institutions are extracted from the Affiliations column

One document is counted once per institution, after institution names are harmonized (for example, "Universitas Bina Nusantara" and "Binus University" are merged into Bina Nusantara University; units below the university level are merged into their parent university). Nine of the 23 institutions are from India.

3.1.5. Contributing countries

India (70) and China (69) are the most productive, but China and Spain are the most influential; Indonesia ranks 5th in productivity (21 documents) but does not enter the top ten in citations.

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Table 6. Top Ten Contributing Countries

Country	TP	Rank	Country	TC	Rank
India	70	1	China	1,541	1
China	69	2	Spain	1,462	2
United States	32	3	United States	924	3
United Kingdom	22	4	United Kingdom	817	4
Indonesia	21	5	India	810	5
Saudi Arabia	14	6	France	743	6
Malaysia	14	7	Serbia	490	7
Taiwan	10	8	South Africa	489	8
Iraq	10	9	Germany	395	9
Jordan	10	10	Italy	373	10

Note: TP = Total Publications; TC = Total Citations.

3.2. *Science Mapping Results*

3.2.1. *Thematic structure: keyword co-occurrence*

Of the 813 author keywords (after the thesaurus), 72 appear at least three times and form four clusters. The green cluster (deep learning for fraud and risk) has the most occurrences (181), while the red cluster (AI in banking) has the most members (26 keywords).

VOSviewer settings: co-occurrence, unit: author keywords, full counting, minimum threshold of 3 occurrences, keyword thesaurus (search terms removed), association strength normalization.

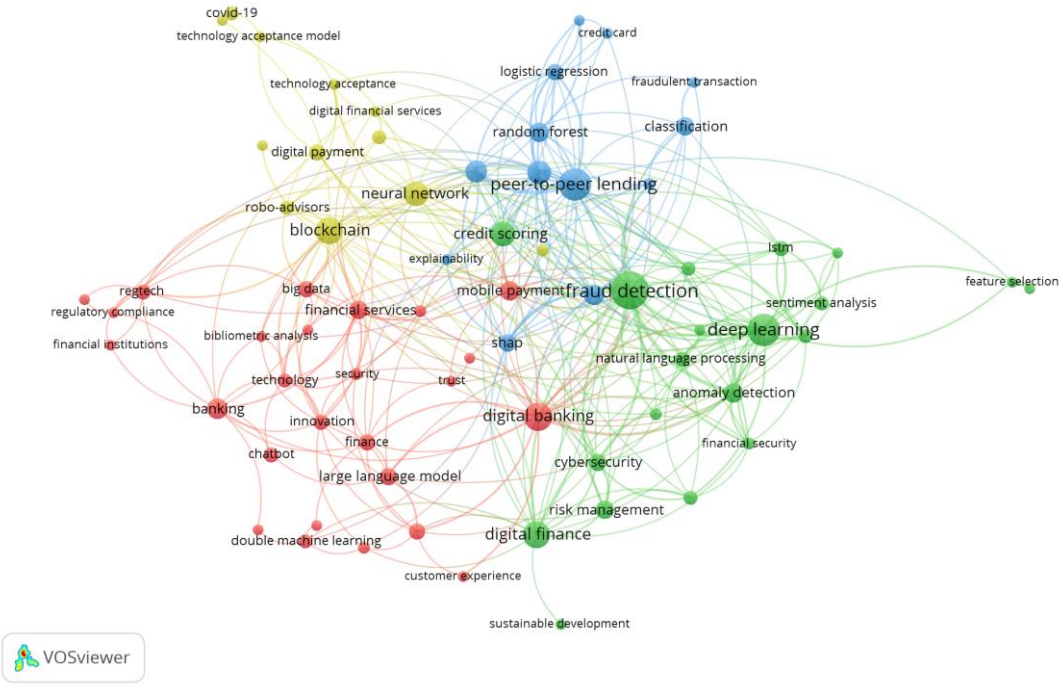


Figure 5. Thematic Clusters of Fintech × AI Research. Source: VOSviewer, 312 Scopus documents, 72 keywords with at least 3 occurrences.

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Table 7. Keyword Cluster Members

Cluster	Theme	Keywords (occurrences)	Items	Occurrences	Average year
1 (red)	AI in banking and financial services transformation	digital banking (20), banking (11), mobile payment (10), financial services (9), large language model (8), generative artificial intelligence (7), big data (7), chatbot (6), regtech (6), innovation (6), double machine learning (5), open banking (4), trust (3), regulatory compliance (3), customer experience (3), others	26	149	2023.5
2 (green)	Deep learning for fraud detection, security, and risk	fraud detection (37), deep learning (27), digital finance (19), credit scoring (16), anomaly detection (10), risk management (9), cybersecurity (8), natural language processing (6), LSTM (6), convolutional neural network (5), reinforcement learning (5), sentiment analysis (5), others	20	181	2023.9
3 (blue)	Machine learning and explainability for credit risk and P2P lending	peer-to-peer lending (27), XGBoost (14), credit risk (12), explainable artificial intelligence (11), random forest (10), classification (9), SHAP (8), logistic regression (7), imbalanced data (4), others	13	114	2022.9
4 (yellow)	Fintech adoption, digital payments, and blockchain	blockchain (18), neural network (16), digital payment (7), robo-advisors (5), financial inclusion (5), covid-19 (5), predictive analytics (4), technology acceptance model (3), cryptocurrency (3), others	12	75	2023.1

Note: the average year is weighted by the number of occurrences. The full list is available in the VOSviewer map file.

Cluster 1: AI in banking and financial services transformation. This cluster discusses AI applications at the institutional and customer levels: digital banking, open banking, regtech, regulatory compliance, trust, and customer experience. Gen-AI (large language model, chatbot) sits in this cluster, meaning that Gen-AI is so far studied as a service tool, not as a risk analysis tool.

Cluster 2: Deep learning for fraud detection, security, and risk. This is the densest and most technical cluster, with fraud detection as the largest node. The architectures used are diverse (LSTM, CNN, attention mechanism, reinforcement learning) for anomaly detection, cybersecurity, and financial crisis prediction.

Cluster 3: Machine learning and explainability for credit risk. This cluster centers on default prediction in peer-to-peer lending using classification models (logistic regression, random forest, XGBoost), handling of imbalanced data, and model explanation with XAI/SHAP. Its average year is the oldest (2022.9), so this cluster forms the foundation of research in this field.

Cluster 4: Fintech adoption, digital payments, and blockchain. This cluster brings together adoption behavior studies (technology acceptance model, robo-advisors) and enabling fintech technologies (blockchain, cryptocurrency, digital payments), including the impact of COVID-19. Financial inclusion enters this cluster with the most recent average year (2025.0).

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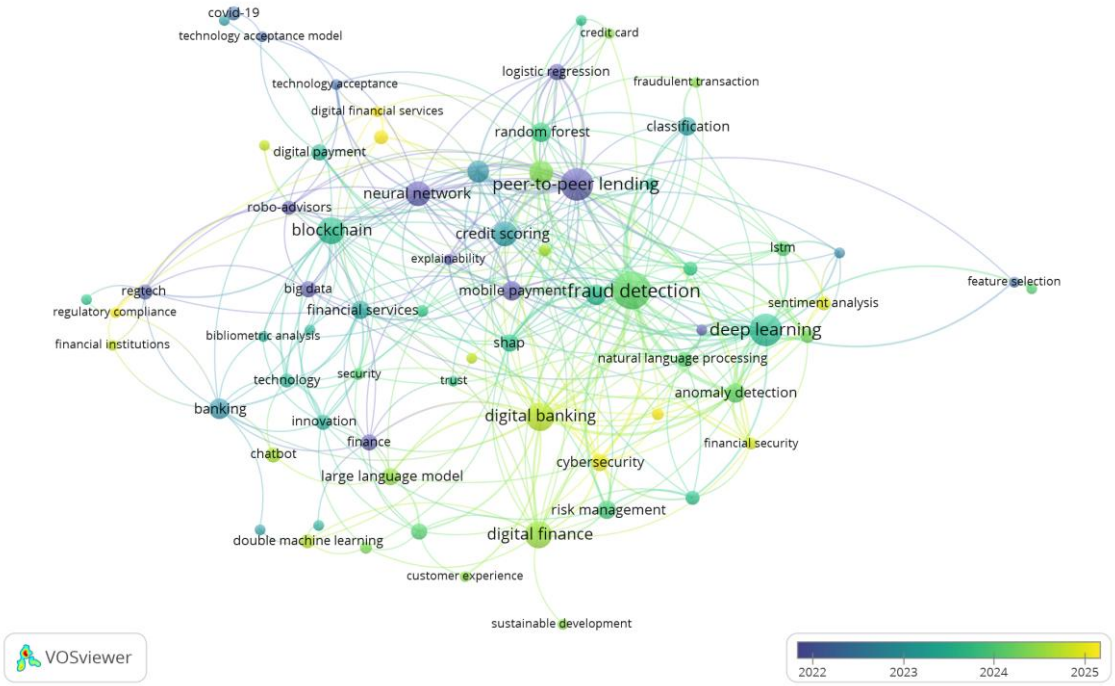


Figure 6. Keyword Trends by Average Publication Year. Source: VOSviewer, overlay visualization (score: average publication year). Lighter colors indicate more recent keywords.

The oldest keywords in the dataset are robo-advisors (2021.2), peer-to-peer lending (2021.3), and mobile payment (2021.3). The most recent are financial inclusion, regulatory compliance, digital financial services, and digital payment systems (all 2025.0), followed by cybersecurity (2024.9) and sentiment analysis (2024.8). The research focus shifts from AI for credit scoring and lending to AI for security, fraud detection, and digital banking services. The color scale covers only 2022–2025 because 75% of documents are published in 2023–2025, so this trend describes themes that are newly emerging in the dataset, not a projection.

3.2.2. Future research directions

The following five gaps are inferred from the position and connectivity of nodes on the map, then checked against co-occurrence counts in the data.

Table 8. Future Research Directions

No.	Gap	Evidence from the map and data	Research question
1	Gen-AI is not yet used for risk analysis	LLM and Gen-AI sit in cluster 1 (services); LLM co-occurs with fraud detection 0 times, credit risk 0 times, credit scoring 1 time	How far does an LLM improve fraud detection and credit scoring compared with existing ML/DL models?
2	Explainability lags behind deep learning	XAI and SHAP sit in the credit cluster (3); XAI co-occurs with anomaly detection 0 times and with deep learning 2 times	How can deep learning models for fraud detection be made explainable and auditable?
3	Regulation is separated from technical models	Regtech and regulatory compliance sit at the edge of cluster 1; they co-occur with deep learning, fraud detection, XAI, or LLM 0 times	How are AI regulatory frameworks translated into fintech model design and validation?
4	Financial inclusion and SDGs sit at the periphery	Financial inclusion (5) is the most recent but small and connected only to credit scoring (2 times); sustainable development is the most isolated node (1 link)	How can AI in fintech expand financial access for unbanked groups?
5	Adoption studies have not yet caught up with Gen-AI	TAM and technology acceptance are relatively early (2022.3); LLM co-occurs with trust 0 times	What determines customer trust in and acceptance of Gen-AI-based fintech services?

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4. Conclusion

This study successfully maps the intellectual landscape, publication growth, and thematic structure of the integration of Financial Technology (Fintech) and Artificial Intelligence (AI) based on 312 Scopus-indexed documents (2015–2025). This academic discourse proves to grow exponentially—with more than 75% of the literature published in 2023–2025—and divides into four main clusters: digital banking transformation, deep learning for fraud detection and risk management, machine learning and explainability for P2P lending, and digital payment adoption. The visual analysis also shows a shift in research focus from classical risk modeling toward cybersecurity, regulatory compliance (RegTech), and financial inclusion.

Theoretically, this study makes a significant contribution by synthesizing the previously fragmented financial technology management literature into a structured scholarly taxonomy. Practically, these findings serve as a strategic guide for decision-makers in the banking, financial services, and insurance (BFSI) sector to prioritize safe innovation, and help regulators design adaptive technology-based supervisory frameworks (RegTech).

Nevertheless, this study has methodological limitations, in that data retrieval is limited to the Scopus database with a precision focus on article titles (TITLE), without a manual relevance screening process (manual title-abstract screening). In addition, there is a natural citation lag constraint on the most recent publications (2024–2025), which means that citation accumulation does not yet fully reflect the long-term academic impact of those newer documents.

To address these limitations, the future research agenda (future research directions) is directed at five main priorities: (1) expanding the use of Generative AI and LLMs from customer service alone to credit risk and fraud analysis, (2) strengthening Explainable AI (XAI/SHAP) models for deep learning transparency, (3) bridging technical AI models with regulatory governance, (4) exploring the role of AI in financial inclusion and sustainable development (sustainable development), and (5) updating adoption studies to measure public trust in AI-based financial innovation.

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