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Utilization of Artificial Intelligence in the Banking Sector: A Bibliometric Analysis

Jyoti Rani[1*], Dalip Raina[2]

[1*]Research Scholar, Skill Department of Management Studies, Shri Viswakarma Skill University, Palwal, India

[2]Assistant Professor, Skill Department of Management Studies, Shri Viswakarma Skill University, Palwal, India

***Corresponding Author: Jyoti Rani**

Abstract

This bibliometric analysis examines the research environment concerning the implementation of artificial intelligence (AI) in the banking sector from 2010 to 2026. The study concentrated on Scopus-indexed publications to recognize prominent research clusters. We employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to evaluate the publications, resulting in 2790 that satisfied the inclusion criteria. The study found 257 words that were only used in the abstracts as well as the titles of the articles. Factor analysis identified five distinct clusters encompassing AI-fintech, risk assessment, cybersecurity, statistical modelling techniques, and marketing and technology adoption, among others. These clusters give a full picture of the complex world of research. The result highlighted two dimensions explaining 44.8% of the variance collectively and thus offers meaningful insights in the field. An evaluation of life cycle predictions shows that after a decade, the adoption of new technologies will change AI into something else. The evaluation also shows that cumulative growth will level off after 2030 and then start to drop from 2030 to 2050. After that, the subject matter score will keep going down, which indicates a shift from growth to saturation. The defined clusters provide significant direction for further inquiries and contribute to the development of research methodology. Future researchers, policymakers, academic community, and professionals in the banking sector can derive meaningful lessons from these findings, which underscore existing research deficiencies and emerging opportunities. This study enhances the bibliometric literature by providing innovative insights on AI-enabled advancements within the banking sector. Furthermore, the findings have substantial practical implications, facilitating the understanding of AI-driven technologies in the enhancement of academic pursuits and financial sector operations.

Keywords: Banking sector, Bibliometric Analysis, Artificial Intelligence (AI)

JEL Classification: G21, O33, C10

1 Introduction

Artificial intelligence (AI) has swiftly revolutionized the worldwide banking industry, enhancing operational efficiency, strategic decision-making, fraud detection, and tailored consumer services (Zhang et al., 2022; Saputri et al., 2025; Pattnaik et al., 2024). Over the past decade, research on AI applications in banking has expanded considerably, encompassing domains such as credit assessment, investment management, regulatory compliance, fraud prevention, and automated customer support systems (Swain et al., 2025; Vuković et al., 2025). Bibliometric studies have identified prominent thematic clusters, collaborative networks, and emerging research trends, underscoring AI's growing role in reshaping financial services worldwide (Swain et al., 2025; Saputri et al., 2025). Despite this progress, significant gaps remain concerning ethical AI deployment, explainable models, regulatory adaptation, and sustainable implementation strategies, highlighting the need for further research. This study employs the bibliometrics to offer a thorough analysis of the present research landscape concerning applications powered by artificial intelligence within the banking sector.

In the Indian banking sector, AI adoption has accelerated in recent years, contributing to operational optimization, enhanced customer engagement, and expanded financial inclusion (Sharma & Singh, 2024). The implementation of AI-driven services, including chatbots, recommendation engines, and predictive analytics is shaped by factors including usability, privacy awareness, and accessibility, emphasizing the importance of user-centred implementation strategies (Babu & Durai, 2023; Sharma & Singh, 2024). AI also supports personalized banking solutions, automates routine processes, and improves the speed and accuracy of decision-making. Notably, AI facilitates financial inclusion by extending services to underbanked and rural populations, addressing challenges related to geographic distance and limited credit histories (Dwivedi & Sahoo, 2025). Comparative analyses indicate that private banks demonstrate higher AI maturity due to competitive pressures and operational flexibility, whereas public sector banks are gradually enhancing their capabilities through policy support and infrastructure development (Singh et al., 2026). Emerging "Green AI" initiatives further integrate sustainability by promoting energy-efficient algorithms and cloud-based platforms, enabling high performance in fraud detection, credit scoring, and operational automation while minimizing environmental impact (Chandran et al., 2025).

Review of latest research highlights AI's strategic significance in credit risk assessment, fraud detection, and decision-making frameworks. Hybrid approaches that combine machine learning with advanced analytical models have been shown to enhance predictive accuracy and strengthen strategic decision support (Goyal et al., 2025). Adoption frameworks for AI tools, including conversational agents, demonstrate that task–technology fit, perceived ease of use, and trust are key determinants of user acceptance (Ali et al., 2025). Broader reviews reveal that AI applications now extend to Robo-advisory services, digital insurance, and financial inclusion, while simultaneously presenting regulatory, ethical, and governance challenges that require careful management (Vuković et al., 2025; Fundira & Mbohwa, 2025). Bibliometric and trend analyses further indicate that AI technologies including machine learning, natural language processing, and predictive analytics are central to digital transformation strategies, enhancing risk management, operational efficiency, and customer engagement (Subburayan et al., 2024; Jafri et al., 2025).

Market analyses underscore the growing economic importance of AI in banking. In 2020, the global AI in banking market was worth $3.88 billion. By 2030, it is expected to be worth around $64 billion, with a compound annual growth rate of 32.6%. Banks are expected to save approximately $447 billion through AI adoption by 2023 (Allied Market Research, 2023; Digalaki, 2022). These trends highlight AI's strategic relevance for maintaining competitiveness, operational resilience, and innovation capacity.

The increasing influence of AI within the banking sector has created a pressing need for research at this intersection. Despite previous studies acknowledging the advantages of AI integration, including increased productivity, higher customer happiness, and novel economic potential, significant research gaps remain. The current literature has inadequately explored the long-term ethical ramifications, encompassing issues associated with data privacy, algorithmic prejudice, and possible worker displacement resulting from automation. Regulatory issues remain inadequately examined, as policymakers strive to reconcile technology advancement with consumer protection and cybersecurity mandates. Moreover, while AI-driven personalization is gaining prominence, its scalability and effects on various consumer demographics necessitate further examination. Given these developments, a systematic bibliometric review of AI research in banking from 2010 to 2026 is essential to synthesize existing knowledge, map key research trends, identify emerging thematic clusters, and provide actionable insights for researchers, policymakers, and banking practitioners. This study aims to address gaps in both global and Indian AI research, offering a holistic perspective on the current landscape, challenges, and future directions for AI adoption in the banking sector.

This bibliometric analysis thoroughly outlines and integrates the intellectual and conceptual framework of research on the implementation of AI in the banking sector, emphasizing key contributions, notable authors, and leading countries in the field (Gujrati & Biradar, 2023; Charmee & Champaneri, 2025). By examining thematic clusters and citation networks, the study uncovers research gaps and emerging areas of inquiry, offering a clearer understanding of global knowledge development and the evolution of AI applications in banking (Saputri et al., 2025; Swain et al., 2025). These insights not only illuminate seminal works and patterns of scholarly engagement but also reveal blind spots and future research directions, thereby supporting academic research, informing policy priorities, and promoting balanced progress toward sustainable digital transformation in banking services (Gujrati & Biradar, 2023; Charmee & Champaneri, 2025). Given the rapid advancement of AI technologies and their profound influence on banking operations, this research aims to provide practical, analytically grounded insights that extend beyond descriptive assessment.

Table 1: Focus of previous bibliometric analysis studies

Sr. No.	Document	Author	Time period	Focus of the study
1	A Systematic Review of The Application of AI in Banks Through Bibliometric Analysis; Research Trends and Patterns	(Swain et al., 2025)	The study reviews literature from (2002 to 2022). N= 1784 papers	To analyse research trends, key themes, and growth of AI applications in banking using bibliometric analysis.
2.	Artificial intelligence and machine learning in finance: A bibliometric review	(Sharma et al., 2022)	The study reviews literature from (1990–2021) N= 2500 + articles.	Analyses research trends, key themes, and applications of AI & ML in finance using bibliometric methods.
3.	AI and Financial Fraud Prevention: Mapping the Trends and Challenges Through a Bibliometric Lens.	(Kumar et al., 2025)	The study reviews the literature from (2000–2023) Papers included: ~1,000+ research articles	Examines research trends, key themes, and challenges of using AI in financial fraud prevention through bibliometric analysis.
4.	Artificial Intelligence in the Indian Banking System: A Systematic Literature Review.	(Singh et al., 2023)	The study reviews the literature from 2(010–2024). Papers included: ~100+ studies	Reviews applications, benefits, and challenges of AI in the Indian banking system.
5.	Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review	(Pattnaik et al., 2023)	The study reviews the literature from 2000–2022 Papers included: ~1,500+ articles	Examines research trends, key applications, and thematic evolution of AI and ML in the financial services industry using bibliometric analysis.
6.	Advancing and Transforming Finance through Artificial Intelligence: Development and Applications	(Soni et al., 2025)	The study reviews the literature from 2005–2024 ~1,200+ research articles	Explores the development, applications, and transformative impact of AI in the finance sector.
7.	Applications of Artificial Intelligence in the Financial Sector: Current Challenges and Future Directions	(Li, 2025)	The study reviews the literature from 2010–2024 Papers included: ~800+ studies	Examines current applications of AI in the financial sector, identifies challenges, and suggests future research directions.
8.	AI ethics in banking services: a systematic and bibliometric review of regulatory and consumer perspectives	(Fundira & Mbohwa, 2025)	The study reviews the literature from (2010–2024) Papers included: ~300+ articles	Reviews ethical considerations of AI in banking, focusing on regulatory frameworks and consumer perspectives using systematic and bibliometric analysis.

9.	A bibliometric analysis of artificial intelligence and machine learning applications for human resource management	(Koştı & Kayadibi, 2025)	The study reviews the literature from (2010–2024) Papers included: ~600+ articles	Analyzes research trends and applications of AI and ML in human resource management using bibliometric methods.
10.	Application of Artificial Intelligence in Banking and Finance: Bibliometric Review and Emerging Research Agenda	(Gujrati & Biradar, 2023)	The study reviews the literature from (2000–2022) Papers included: ~1,200+ articles	Examines AI applications in banking and finance, identifies research trends, and proposes an emerging research agenda using bibliometric analysis.

Note: Author's Elaboration

To address this gap, our study does a bibliometric analysis to analyse the research landscape. We conduct a comprehensive analysis of academic publications, citations, and themes, referencing the study of (Goodell et al., 2021; Pattnaik et al., 2021; and Baker et al., 2022). We explicitly examine the following research questions (RQs) to provide a comprehensive overview of the literature on AI applications in the banking sector.

RQ1. What annual publication trends and growth rate, citation trends with subsequent influence in the banking sector?

RQ2. What is the research productivity pattern in terms of leading authors, publication volume, and influential journals?".

RQ3. What are the frequently discussed themes and emerging trends?

RQ4. What is the direction for future research?

2 Research Methodology

The review was executed in accordance with the PRISMA protocol, which offers a thorough framework for performing systematic reviews and meta-analyses in a transparent, reproducible, and exhaustive manner (R. Raman et al., 2023). To address the research gaps identified from literature review, the study employs a bibliometric analysis using data retrieved from Scopus database from year 2010-2026.

2.1 Database selection

The initial phase of data collection involved identifying an appropriate source to conduct a systematic review of the literature (Khan et al., 2003; Agrifoglio et al., 2020; Tranfield et al., 2003; Xiao & Watson, 2017; Yeung, 2019). This process began with the selection of a suitable database and the determination of relevant keywords, informed by a comprehensive examination of prior studies. Scopus was chosen as the primary bibliographic database (Pranckutė, 2021), given its reputation as a leading platform for systematic literature reviews. Its advantages include the delivery of superior metadata, dependable citation tracking, and comprehensive coverage of academic outputs, including journals, conference proceedings, and books (Baas et al., 2020; Visser et al., 2021). Complementary databases were also employed to ensure broader access to academic publications (Mongeon & Paul-Hus, 2016; Singh et al., 2021), thereby enhancing the inclusion of high-quality sources (Harzing & Alakangas, 2015). The selection of keywords was guided by insights from earlier reviews, with particular emphasis on capturing diverse business functions and a focused attention on the banking sector (Loureiro et al., 2021; Verma et al., 2021; Borges et al., 2021; Bavaresco et al., 2020).

The second stage employs a quantitative bibliometric approach, producing representative syntheses of extensive bibliographic datasets to facilitate the analysis (Broadus, 1987; Groos & Pritchard, 1969; Cobo et al., 2011; Gutiérrez-Salcedo et al., 2017). To know the contributions for research constituents to a specific field of study performance analysis is conducted (Mas-Tur et al., 2018; Donthu et al., 2021), whereas to know the relationships and interactions between research constituents the science mapping is performed (Öztürk et al., 2024). Depending on the aim of the research and the research questions, researchers can do one or both.

2.2 Selection of Bibliometric tools

For this study, we employed the Biblioshiny package within the Bibliometrix, framework in R Studio, along with VOS viewer, to conduct science mapping and performance analysis (Tiwari et al., 2022; Aria & Cuccurullo, 2022; Bhat et al., 2023; Tamphu et al., 2024). Although a range of bibliometric software applications, such as CiteSpace, HistCite, SciMAT, Gephi, R Studio, and VOSviewer which are available for data visualization and analysis, the choice of tool typically depends on the specific analytical requirements of the research (Derviş, 2020). Bibliometrix is an open-source platform designed for comprehensive mapping in scientific studies. Its continuous development and compatibility with other R-based statistical programs have contributed to its widespread adoption and relevance across descriptive, network, and bibliometric analyses (Yadav & Banerji, 2023). Through the Biblioshiny web interface, data can be imported, transformed into data frames, filtered, analysed, and graphically represented for sources, authors, and documents, thereby simplifying the research process (Farooq, 2022).

2.3 Search String

The relevant body of literature was compiled utilizing the search parameters: TITLE-ABS-KEY ("Artificial Intelligence") AND TITLE-ABS-KEY ("Banking"). These terms were deliberately chosen to capture a broad spectrum of publications addressing the application of artificial intelligence within the banking sector, thereby ensuring the creation of a comprehensive dataset.

2.4 Inclusion / Exclusion criteria:

The search strategy also employed specific filters:

2.4.1 Selection process

The research acquired bibliographic data from 2010 to 2026, including authors, publication years, and citations, by downloading search results in CSV format through the Scopus database export feature. The mapping of knowledge structures, along with the identification of co-authorship networks and emerging research hotspots, facilitated a systematic framework robust enough to support an in-depth examination of scholarship on AI within the banking sector.

The selection was organized into three stages:

Stage I: Identification of relevant documents

Research articles pertaining to AI and the banking industry were sourced from the Scopus bibliometric database. The search strategy employed the terms “Artificial Intelligence” and “Banking Sector,” applied across titles, abstracts, and keywords. This initial query yielded a total of n = 2790 documents. Recognizing that not all retrieved records would fall within the precise scope of the study, additional screening was conducted using predefined filters to ensure the inclusion of only the most relevant publications.

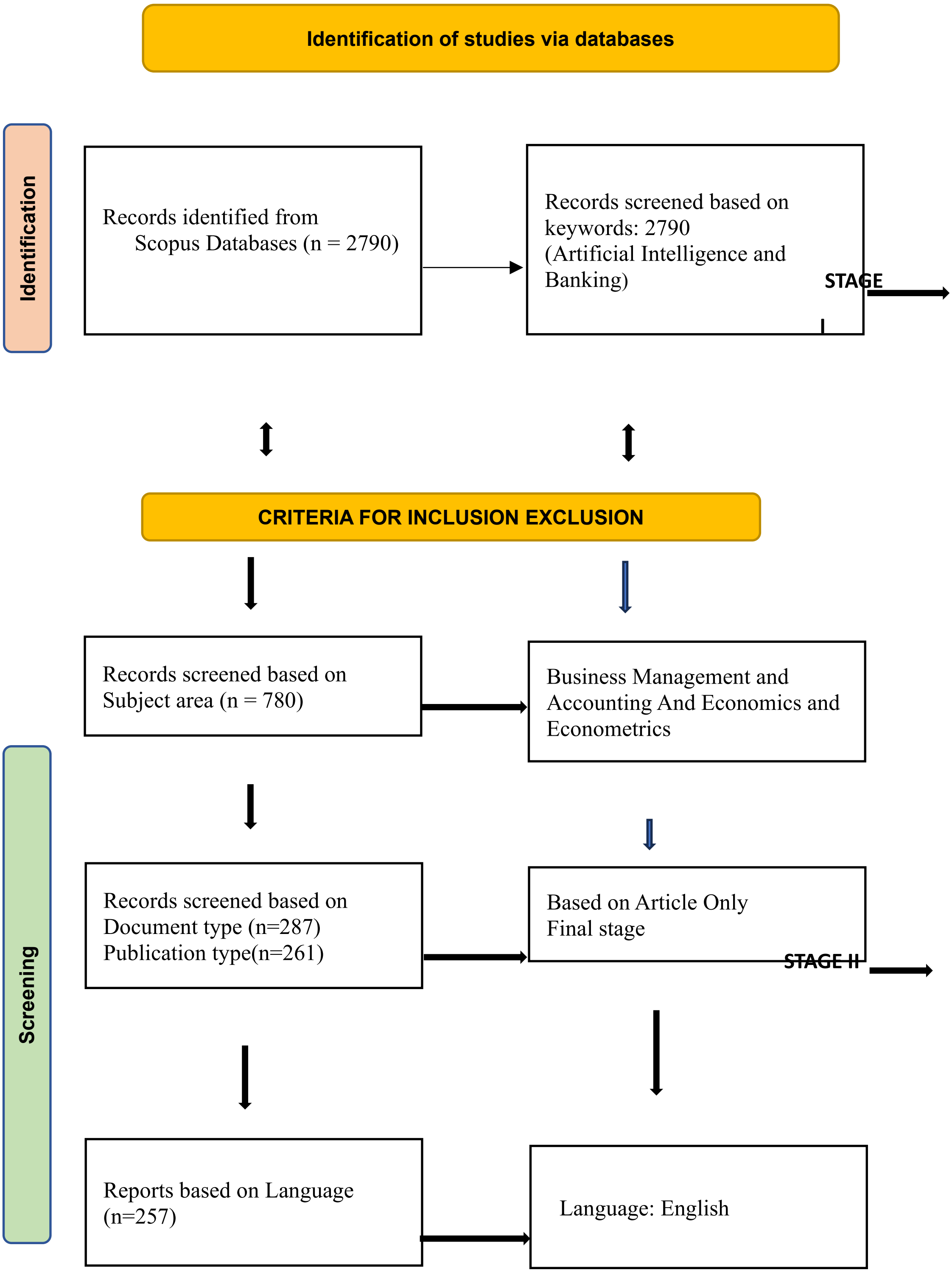
Stage II: Screening of documents

A multi-stage filtering procedure was applied to refine the dataset and ensure alignment with the study’s objectives. In the first step, the scope was restricted to publications classified under Economics, Econometrics, and Finance and Business, Management, and Accounting Business, as illustrated in Figure 1. Next, only peer-reviewed journal articles published in English and available in their final versions were retained. This process reduced the dataset to 780 documents. To further guarantee quality, an additional manual screening was conducted to confirm the relevance of these works to research on AI applications in the banking sector.

Stage III: Final selection.

Following this comprehensive screening, 257 documents were identified as highly pertinent to the literature on AI in banking. Each article was manually verified, and all were found to contribute meaningful insights. These selected publications formed the basis for the subsequent bibliometric analyses.

2.5 Prisma Framework



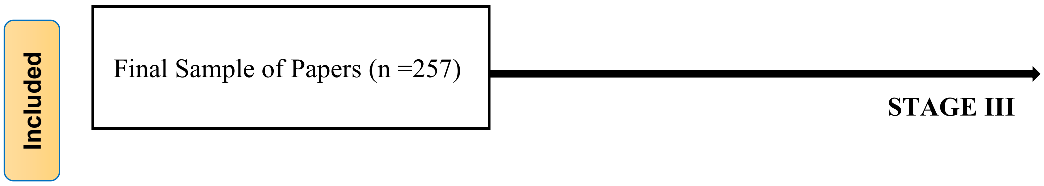


Figure 1: PRISMA Flow diagram depicting the search procedure for bibliometric analysis.

Note: Author's Elaboration

Source: Page MJ, et al. BMJ 2021;372: n71. DOI: 10.1136/bmj.n71./

3 Results and Discussion

Our review of the literature has produced significant results that offer important information about the present state of the discipline of study. A condensed overview of the outcomes is provided below. In order to accomplish these goals, we utilized the Scopus database to analyse the query key bibliometric. The research data were obtained from the Scopus database and analysed utilizing the R software, R Studio version, through the web interface Biblioshiny.

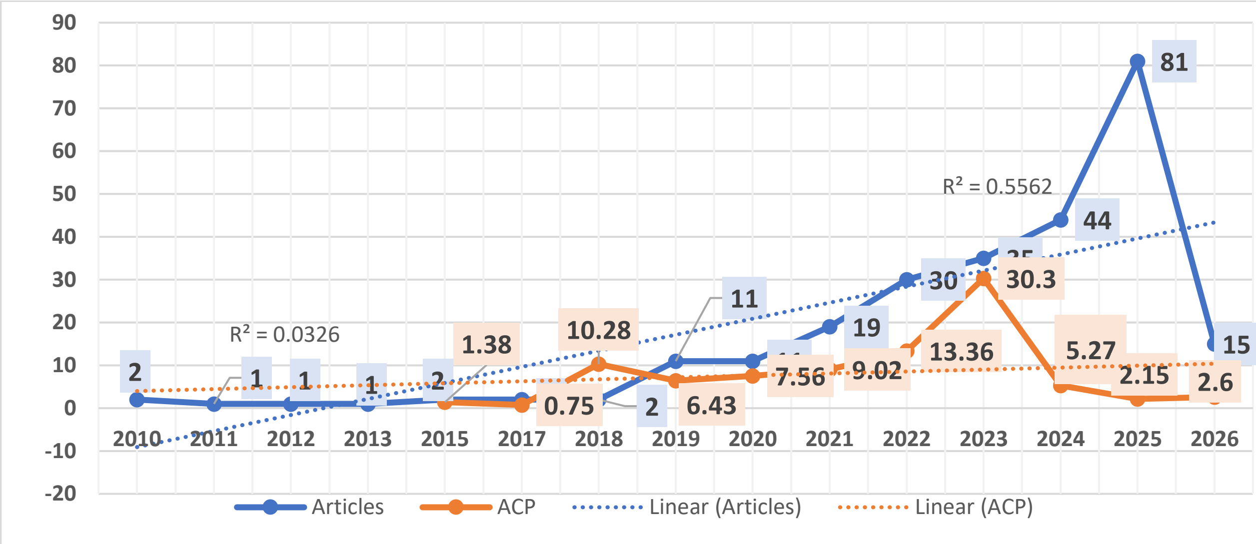
3.1 Key Information about the Dataset

The dataset spanning 2010–2026 highlights a rapidly growing and globally significant research domain, comprising 257 publications distributed across 160 sources, reflecting substantial disciplinary diversity and interdisciplinary engagement. The field demonstrates a remarkable annual growth rate of 13.42, underscoring its dynamic and emergent nature, while the 2.96 % average document age of years attests to the contemporary relevance of the topic. With an average of 38.7 citations per document, the research exhibits notable scholarly impact. The extensive breadth of keywords 396 Keywords Plus and 879 author-assigned, illustrates the conceptual richness and thematic comprehensiveness of the field. Authorship patterns indicate a strong culture of collaboration, with 836 authors contributing an average of 3.37 co-authors per paper. Additionally, the substantial proportion of international collaborations (24.51%) emphasizes the global scope and interconnectedness of this research area. Collectively, these metrics position the domain as a highly dynamic, collaborative, and influential field, steadily gaining academic traction and shaping contemporary scholarly discourse.

3.2 Annual Scientific Production, and Average Citations Per Document

The information shows that during the observed time, scientific publications increased steadily and more quickly. This upward trajectory, started with just two articles in 2010, one article till 2015 and no publications in 2014, continued with 44 papers in 2024 and reached a peak of 81 in 2025, indicating the field's increasing academic trend showed via trend line in the graph. Even though the number of publications declined dramatically from 81 to 15 in 2026, indicating a significant drop in research output. Such a decline may also reflect evolving research priorities or saturation within the domain, warranting further investigation into the underlying drivers of this downward trajectory**.** A marked decline is observed in 2026, which is likely attributable to incomplete data collection for the current year. Taken as a whole, the pattern indicates a sustained increase in scholarly attention to the subject up until very recently. The average citation per document articulated low citation counts with R^2= 0.0326 showing only 3.26% of the data is relevant to the topic and rest 96.74% is influenced by other factors. However, the annual scientific production represents R^2= 0.5562 which depicted that 56% of production at annual level is relevant to the area of research. It highlights that in the year 2023 citations are in peak with 30.3 citations per article then again dropped to 5.27 citations in next year (refer figure 2).

Figure 2: Annual Scientific Production & Average Citation per Document with Trend Line



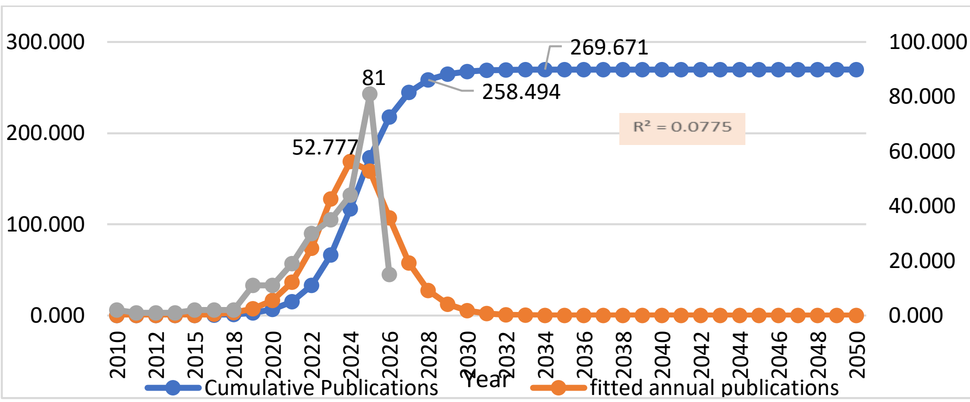
Note: Author's Elaboration

Source: Scopus

3.3 Life Cycle- Annual Publications and cumulative growth curve

This dataset tracks annual publications from 2010 to 2050, with "Fitted annual publications" as model predictions. Actual totals reached 257 publications over 17 years, and the fitted publications sum of 269.74 due to a 2025 surge (81 actual vs. 53 fitted). Fitted values peak around 2023-2024 at ~56 publications before declining, indicating a growth model like logistic or exponential that naturally tapers after saturation. Actual values show slow start, acceleration post-2020, and outlier peak in 2025 (81). In 2026 actual publications are 15, this might mean the boom is cooling or data is still coming in is projection**.** AI-banking publications hit maximum growth in year 2025 as tm_year value (2024.31) means the fastest growth happened in 2024 before slowing down. However, the predicted annual publications represent R^2= 0.77 which depicted that 77% of production at annual level is relevant to the area of research (refer figure 4). The cumulative growth curve shows total publications building up over time in a classic S-shape: slow start, fast growth, then stabilize. Figure 3 presents rapid post-2020 expansion followed by plateauing, indicates AI-banking research's approach to field saturation.

Figure 3: Life cycle of annual publications and cumulative growth curve



Note: Author's Elaboration

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Source: Scopus

3.4 Country wise distribution in AI and banking

Analysis of country-wise contributions in AI and banking research shows that the United Kingdom leads in overall influence, with the highest total citations (3552) and strong average citations per article (507.4), indicating both high output and impact. India, while producing the largest number of publications (99), has a lower average citation per paper (25.5), reflecting high quantity but moderate impact. Countries like Indonesia (92.7) and France (77.5) produce fewer studies but with very high average citations, suggesting their research is highly influential despite lower output. Overall, the data highlights a quantity-versus-quality dynamic, emphasizing the need for collaborative and context-specific studies to strengthen both the reach and impact of AI research in banking (refer table 2).

Table 2: Top 10 country wise publications and citation impact

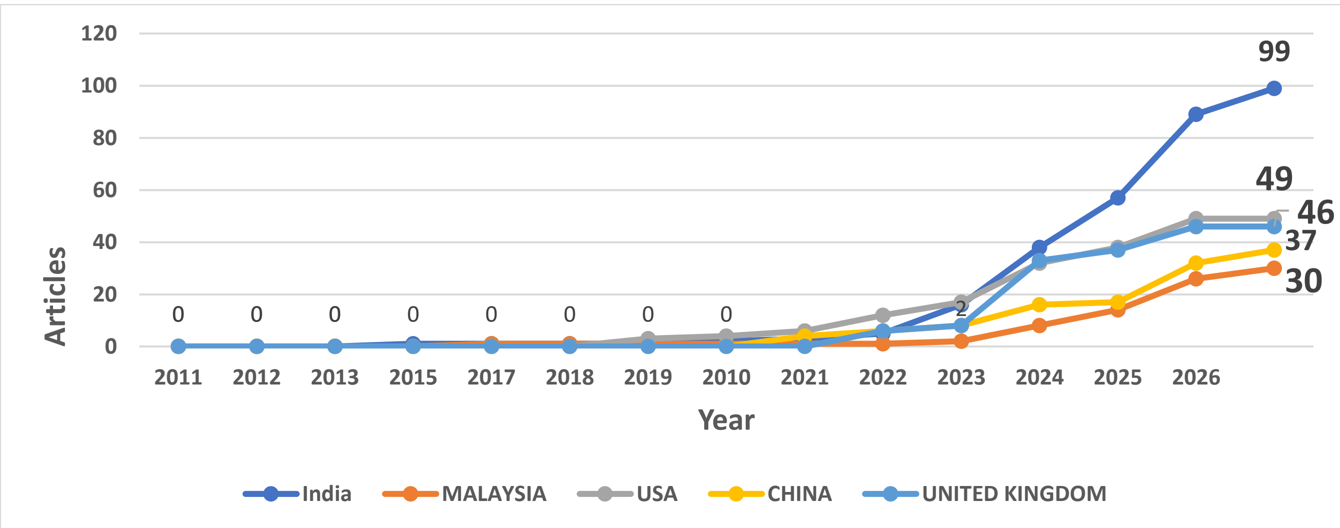
Country	TC	Average article citation	Number of Publications
The United kingdom	3552	507.4	46
China	787	35.8	37
India	689	25.5	99
Usa	686	68.6	49
Spain	451	64.4	24
Australia	379	47.4	20
France	310	77.5	24
Malaysia	281	35.1	30
Indonesia	278	92.7	15
United Arab Emirates	228	45.6	12

Note: Author's Elaboration

Source: Scopus

The study highlights that India (99) has the most research impact from 2010 to 2026, with the highest average number of citations per article. The USA (49), the UK (46), China (37), and Malaysia (20) follow. This shows that India does a lot of important work, but new countries like the US, UK, and China are doing more work and getting more attention in AI and banking research. Future studies could look into partnerships and regional drivers to make the impact of global research even bigger.

Figure 4: Countries wise number of publications



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Note: Author's Elaboration

Source: Scopus

3.5 Most Global Cited Documents

The dataset highlights citation indicators for several influential publications, including measures such as total citations, annual citation rates, and normalized citation counts. Among the most prominent works, Dwivedi et al., 2023, International Journal of Information Management records an exceptional 3,287 citations with a normalized TC of 27.12, reflecting sustained scholarly engagement. Similarly, Flavián et al., 2022, Journal of Service Management demonstrates considerable impact with 346 citations and a normalized TC of 5. Xu, 2020, Australasian Marketing Journal is notable for its 282 citations and a normalized TC of 5, indicating strong influence relative to its publication year. In addition, Trivedi, 2019, Journal of Internet Commerce achieved 281 citations with a normalized TC of 5.46, underscoring its relevance. Collectively, these studies represent diverse areas of research strength and significant contributions to the field. It also identifies emerging studies and authors from 2022–2023 with growing influence, suggesting potential future research leaders. Moreover, the study underscores underexplored areas, including trust, explainable AI, and ethical AI, particularly in emerging markets, revealing critical research gaps. By visualizing impact, productivity, and normalized influence, this approach offers a more comprehensive framework for identifying both established and emerging contributions in AI-driven banking research.

Table 3: Top 10 Most Global Cited Documents with normalized total citation

TC	Normalized TC	Author (s)	Title
3287	27.12	Dwivedi et al., (2023)	So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI.
346	5.18	Flavián et al., (2022)	Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness.
282	5.33	Xu, (2020)	AI Customer Service: Task Complexity, Problem-Solving Ability, and Usage Intention.
281	5.46	Trivedi, (2019)	Examining the Customer Experience of Using Banking Chatbots and Its Impact on Brand Love: The Moderating Role of Perceived Risk.
280	5.18	Ashta, (2021)	Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance.
225	4.16	Manser Payne et al., (2021a)	Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms.
205	3.79	Manser Payne et al., (2021b)	Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems.
204	3.05	Wijayati et al., (2022)	A study of artificial intelligence on employee performance and work engagement: the moderating role of change leadership.
201	3.91	Jakšič, (2019)	Relationship banking and information technology: the role of artificial intelligence and FinTech.
200	1.65	Rahman et al., (2023)	Adoption of artificial intelligence in banking services: an empirical analysis.
180	2.69	Lee et al., (2022)	Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: the intelligent and anthropomorphic perspectives.

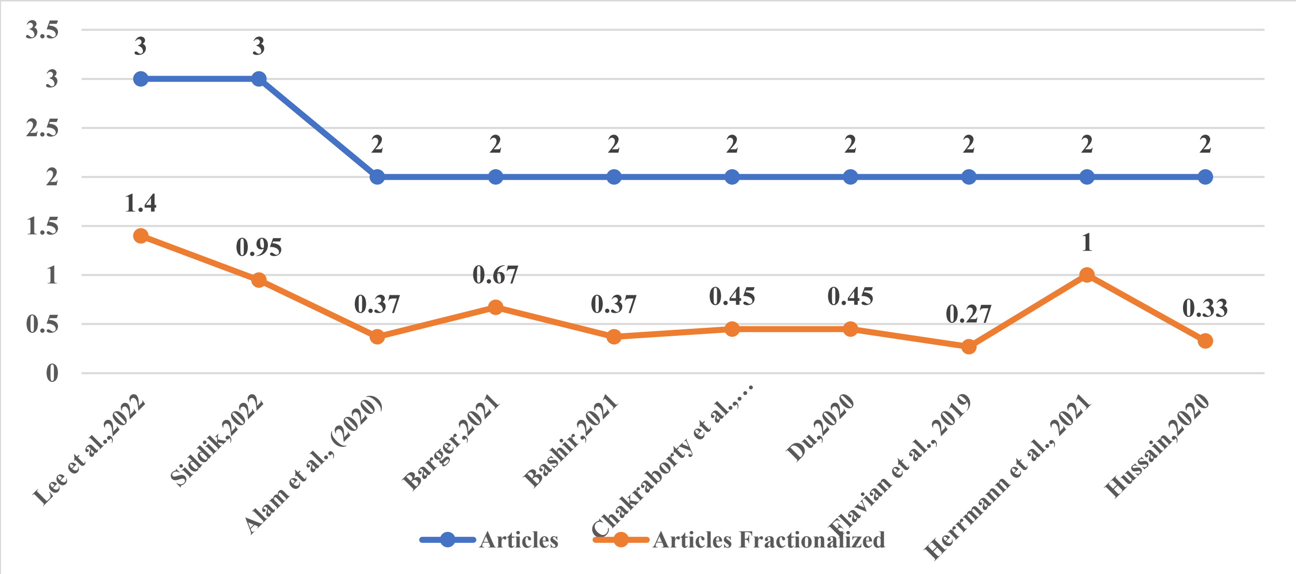
Note: Author's Elaboration

Source: Scopus

3.6 Most Influencing Authors

The analysis of author contributions in AI and banking research highlights both prolific and high-impact contributors. Lee et al., (2022) and Siddik, (2022) lead with three articles each and substantial fractionalized contributions of 1.4 and 0.95 respectively, while Herrnann, (2021) shows full contribution in co-authored works. Authors such as Barger, (2021) and Chakraborty, (2021) also make significant contributions, whereas Flavián et al., (2022) and Hussain, (2020) have smaller fractionalized shares, reflecting collaborative input. Including publication years emphasizes recent activity and emerging contributors shaping current AI-banking research trends. They play a key role in shaping research trends and emerging themes in AI and banking.

Figure 4: Highest Contributing Authors



Note: Author's Elaboration

Source: Scopus

3.7 Journal Matrix with Total Production and Citation

Impact Matrix is widely used to evaluate the productivity and significance of authors, journals and institutions. The h-index, g-index, and i-10 index have all increased over time, indicating that the research is exerting a gradually stronger impact. The h-index shows consistent scholarly impact, the g-index highlights the weight of highly cited contributions, and the i10-index tracks broader recognition. Table 4 illustrate that International Journal of Bank Marketing having 10 articles per year with 876 total citation is a significant number and Journal of Risk and financial management with 8 articles per year and 160 citation score is the most impactful journals being most cited and having continuous contribution which is widely recognised. The third rank is of Cogent Business and management it has only 5 publications but they are effective as citation score is 71 which is sufficient to evidence it importance. Overall, this analysis highlights core, high-impact journals, identifies emerging outlets, and helps map publication trends, guiding researchers toward reliable and influential sources for AI and banking studies.

Table 4: Top 10 Journals with Highest Publications, impact factor and Citation Scores

Source	h_index	g_index	m_index	TC	NP
International Journal of Bank marketing	10	12	2	876	12
Journal of Risk and financial management	8	10	1.6	160	10
Cogent business and management	5	7	0.625	71	7

Journal of financial services marketing	4	4	1	157	4
Banks and bank systems	3	5	0.42857	92	5
Economics and business review	3	3	0.6	22	3
Journal of research in Interactive Marketing	3	3	0.33333	558	3
Strategic change	3	4	0.5	361	4
Technological forecasting and social change	3	4	0.42857	105	4
Decision support systems	2	2	0.11765	128	2

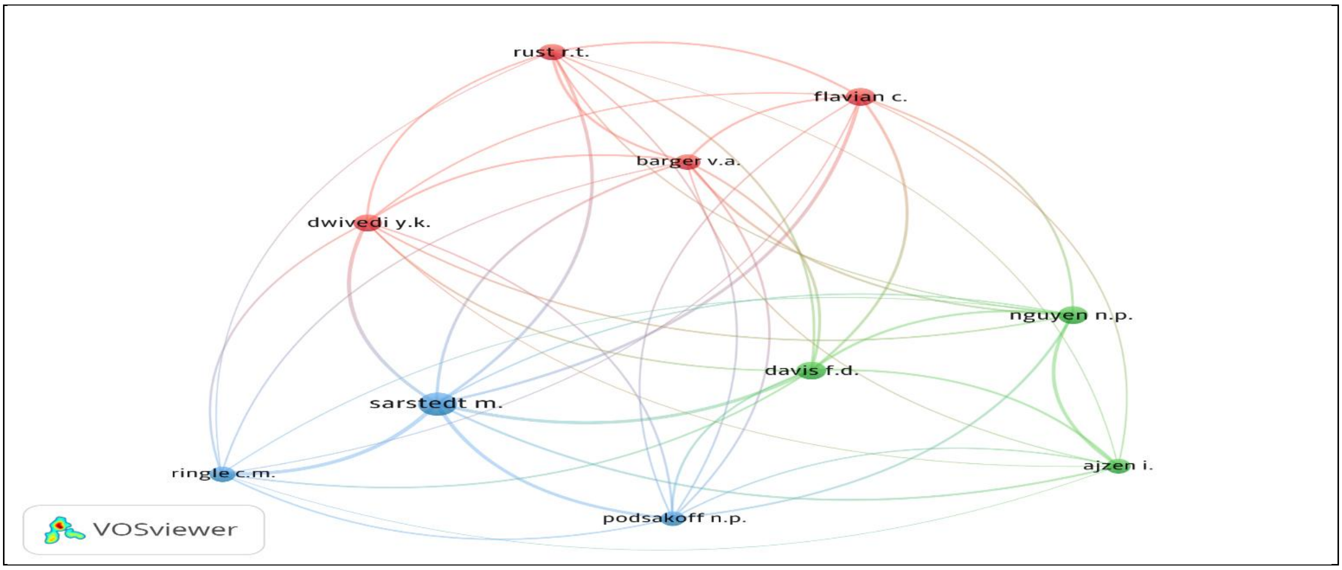
Note: Authors Elaboration

Source: Scopus

3.8 Co- Citation Analysis

Researchers are represented in the co-citation network nodes whose size indicates citation centrality. Figure 13 illustrates the clustering of authors and reports their betweenness, closeness, and PageRank values, which highlight their influence and centrality within the network. In Cluster 1, Ringle, (2019) and Podsakoff et al., (2003), demonstrate notably high betweenness scores (51.13 and 47.74) and identical closeness values (0.031), underscoring their pivotal roles in bridging different nodes and maintaining strong connectivity within the cluster. Overall, the visualization provides valuable insights into the structure of research collaboration, identifying leading scholars, cohesive collaborative groups, and potential areas where enhanced connectivity could stimulate further academic activity.

Figure 5: Co- Citation Analysis of Authors/ Collaborative Network



Note: - Author's Elaboration (Source: - Scopus)

3.9 Three Field Plot

This is bibliometric visualization technique to simply show how the Authors, keywords and cited references are related to each other. The three-field plot links the cited references (CR), author (AU), and author-assigned keywords/topics (DE) through grey flows, with the size of each rectangle indicating the number of associated publications. The middle field (authors) is the main focus, showing which researchers connect specific journals to particular key topics in AI and banking, highlighting both foundational knowledge and emerging research gaps.

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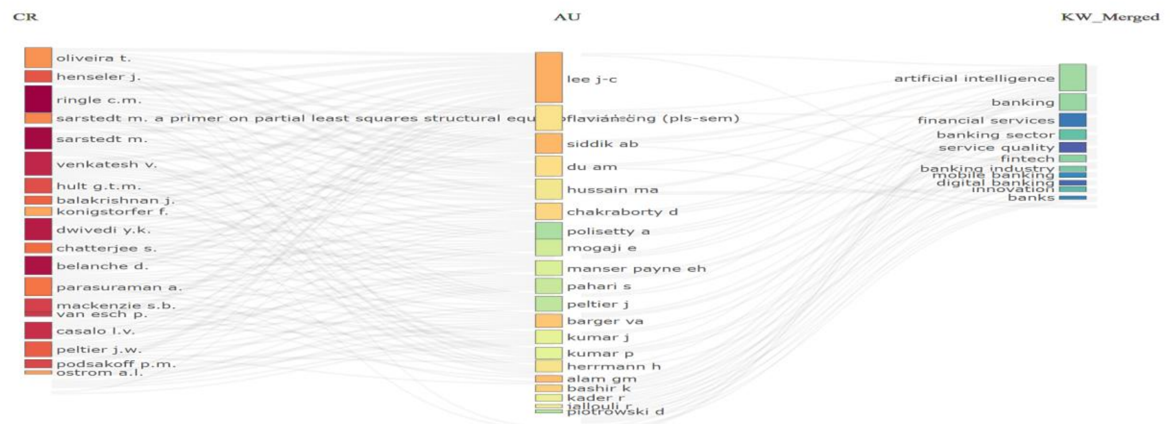
This Three field plot reveals distinct thematic clusters within the research field. Lee et al., (2022) work on AI, is anchored by the influential reference of Oliveira et al., (2014), indicating that this author group is building on core AI literature. Siddik, (2025) and Henseler j. are strongly associated with banking, highlighting their focus on banking research. Siddik, (2025) and ringle, (2019) are linked to financial services, suggesting their contribution to finance-oriented or banking-related studies. Sarastedt et al., (2015) cluster around banking sector, showing their specialization in banking or financial-sector research. Subsequently, there are Alam et al., (2020); Barger et al., (2022); Bashir, (2021); Chakraborty et al., (2022), Flavian et al., (2019); and Hermann et al., (2021) whose scores are arranged in accordance with the sequence of author names. All listed authors are directly connected to the study's theme and the references supporting the article. On the right side of the thematic representation, AI shows highest trend (light green), followed by banking, financial services, banking sector, service quality, fintech, mobile banking, digital banking, and innovation. Overall, the figure 7 shows how references, keywords, and authors are related. It shows well-known areas (like AI adoption models, econometric tools) and areas that haven't been studied much yet (like ethical AI, trust, regulatory frameworks, or cross-country studies).

Figure 7: Three Field plot analysis



Note: Authors Elaboration

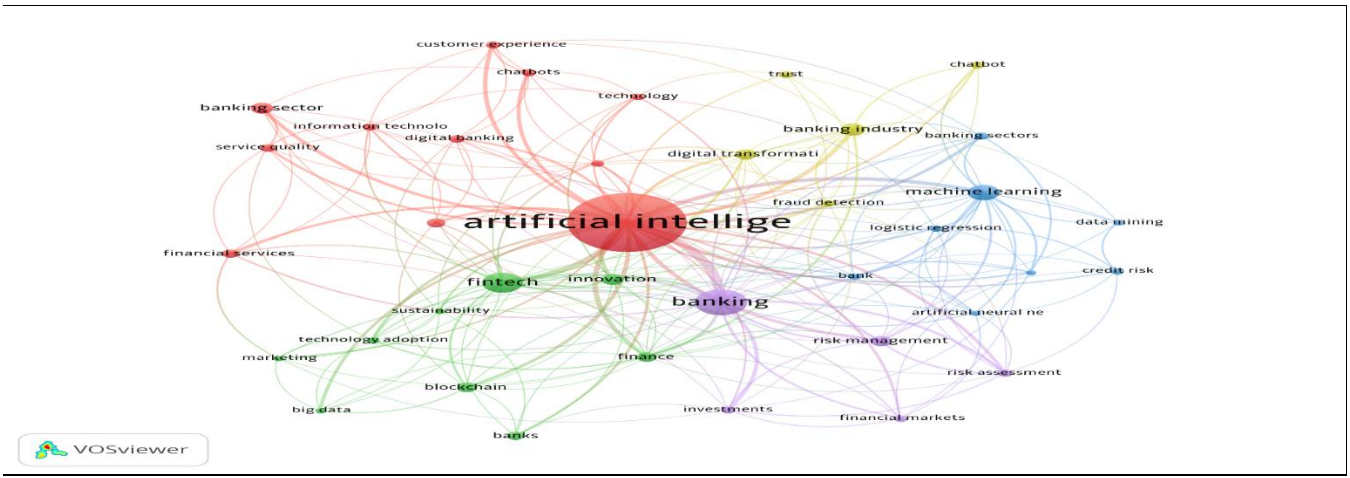
Source: Scopus

3.10 Co- Occurrence Network/ Co- Word Analysis

The co-occurrence density network represents the principal or highly concentrated theme of the research. The most prominent key word of the dataset coloured as red is artificial intelligence which is the heart of the research.

Keyword and trend analysis reveals how research priorities have shifted over time, drawing attention to both emerging areas and established themes. Monitoring the frequency of recurring keywords makes it possible to trace the direction of the field and highlight gaps that remain underexplored. The findings indicate a transition from foundational terms such as machine learning toward newer concepts like digital transformation, green finance, and technology adoption. This progression signifies an expanding focus within AI-banking research, with contemporary studies increasingly prioritizing sustainability and inclusion in accordance with global development goals.

Figure 8: Co-Occurrence Network for Connection Building



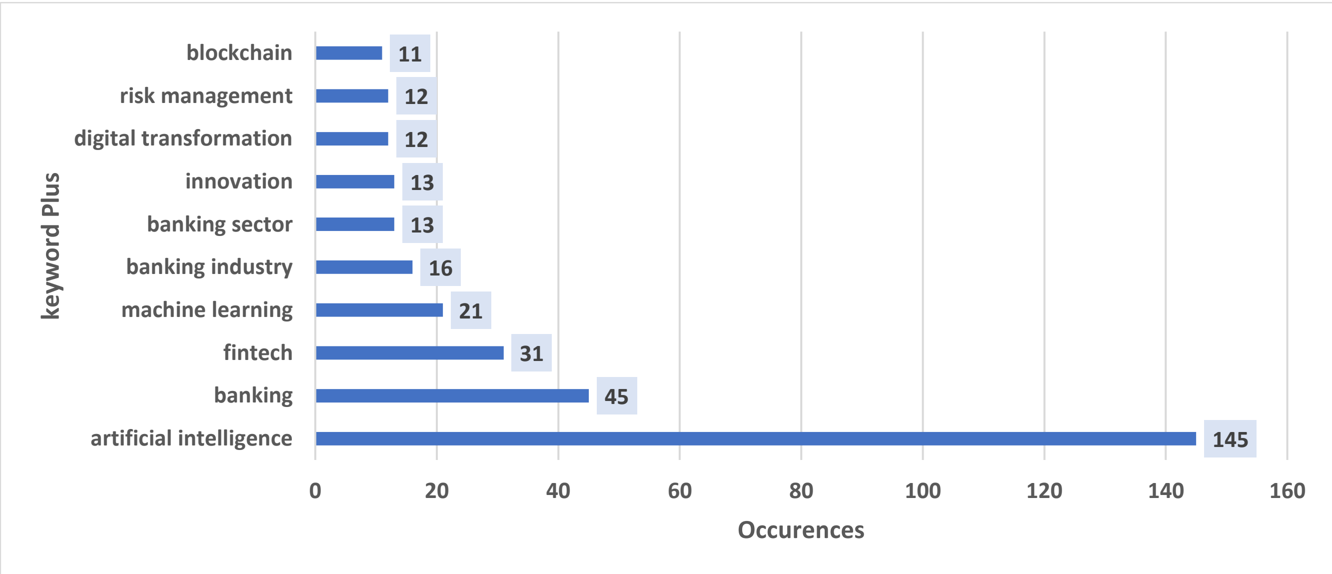
Note: Authors Elaboration

Source: Scopus

3.11 Most relevant words

Keyword analysis shows that AI, banking, fintech, and machine learning dominate the field, highlighting core research themes and emerging trends in digital banking services. Artificial intelligence emerges as the most frequently used keyword, appearing 145 times, followed by banking with 45 mentions. Other significant terms include Fintech (31), machine learning (21), banking industry (16), innovation (13), and digital transformation (12). Additionally, domain-specific terms such as risk management (12), blockchain (11), and financial services (11) feature prominently. Collectively, these findings underscore the central role of technological advancements, pointing to emerging research opportunities in trust, ethical AI, and digital banking innovation in shaping research within the banking sector.

Figure 9: Most relevant words



Note: Author's Elaboration

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Source: Scopus

3.12 Conceptual Thematic Map

The thematic map is a combination of four distinct clusters. The most relevant topics in the field, derived from authors' keywords, were visualized on a two-dimensional thematic map. **Figure 16** shows the thematic map which provides a 2D view of the developments of themes relating to the area of study. The X-axis represents centrality (i.e., relevance and connectivity of a theme with others), while the Y-axis depicts density (i.e., the internal development and maturity of the theme).

These are four quadrants in the thematic map from which the study can analyse by a tabular presentation in table 3:

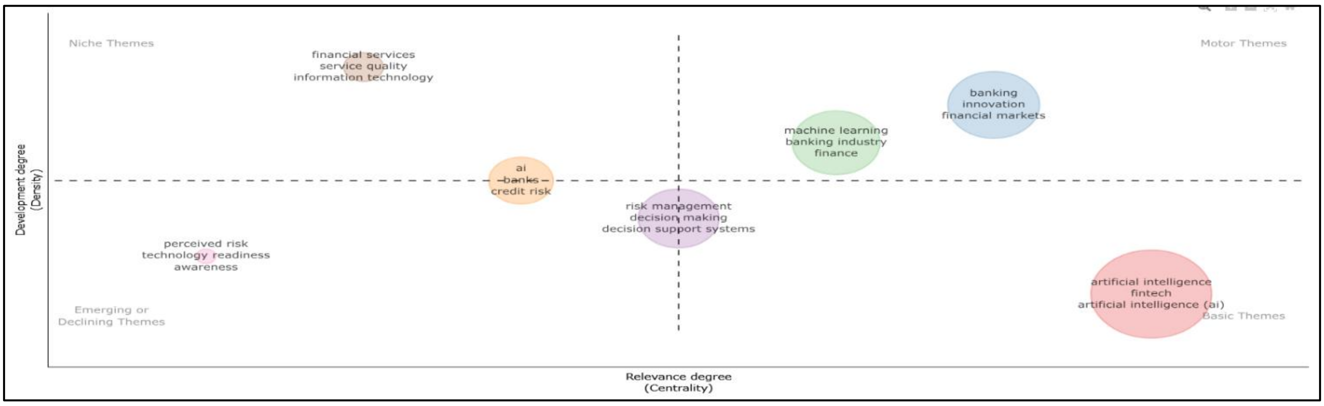
Table 5: Conceptual Thematic Quadrants

Sr. No.	Quadrants	Description	Authors Keywords	Associated Clusters
1	Motor Theme (Top –Right Quadrant)	Thoroughly developed central themes suitable for further research.	Banking, Machine Learning, innovation, AI	Banks, ai, Investments
2	Niche Theme (Top –Left Quadrant)	Specialized topics ideal for deep thematic study.	Financial services, service quality, information technology	Banking sector, machine learning
3	Basic Themes (bottom –Right Quadrant)	Foundational for research but require greater innovation or integration with emerging tools.	Artificial Intelligence, Banking sector, Banking Industry	Fintech, Artificial Intelligence, Digital Transformation
4	Emerging or Declining Theme (bottom –left Quadrant)	Volatile, innovation-rich themes linked to finance and policy, ideal for research.	Fraud detection, Trust	Blockchain, Cyber security

Note: Author's Elaboration

Emerging Technologies contains blockchain, cyber security. Although not a conventional risk category, it underscores the influence of emerging AI-enabled technologies on banking. It is somewhat unrelated but engages with risk (e.g., blockchain utilized for fraud mitigation). Overall, trust emerges as an important but developing theme for adoption of AI driven banking, yet requiring deeper theoretical framing and empirical validation in the context of AI in banking (Ni, 2024; Srivastava & Sharma, 2024; Nagaraj, 2025). Additionally, AI explainability, ethical use, and governance are recognized as emerging themes that need further research and conceptual support, especially as regulators and practitioners emphasize transparency and responsible AI deployment in banking.

Figure 10: Conceptual Thematic Map



Note: - Authors Elaboration (Source: - Scopus)

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Source: - Scopus

3.13 Factor Analysis

The study adopted Multiple Correspondence Analysis (MCA) for the data and developed a conceptual structure with two dimensions focus on research in the area of banking sector. Dimension 1 (30.38%) reflects that there is a clear transition from the traditional analysis to technology driven analysis in the area of banking & finance. On the other side dimension 2(14.42%) highly the methodological rigor with the focus on application omitted domain & area of the research in the field.

The distribution of keyword among the clusters provides the level of evolution and the maturity with interconnected cluster in the research field.

Cluster 1: AI- Fintech and Digital Banking – The keywords like artificial intelligence, machine learning, fintech related innovation, adoption of technology, service quality and sustainability reflects that the research cluster is most emerging and synchronous one. There is focus on the digital innovation in the area of banking. The combination of machine learning with sustainability represents that there is focus on the innovation -driven research in the banking area.

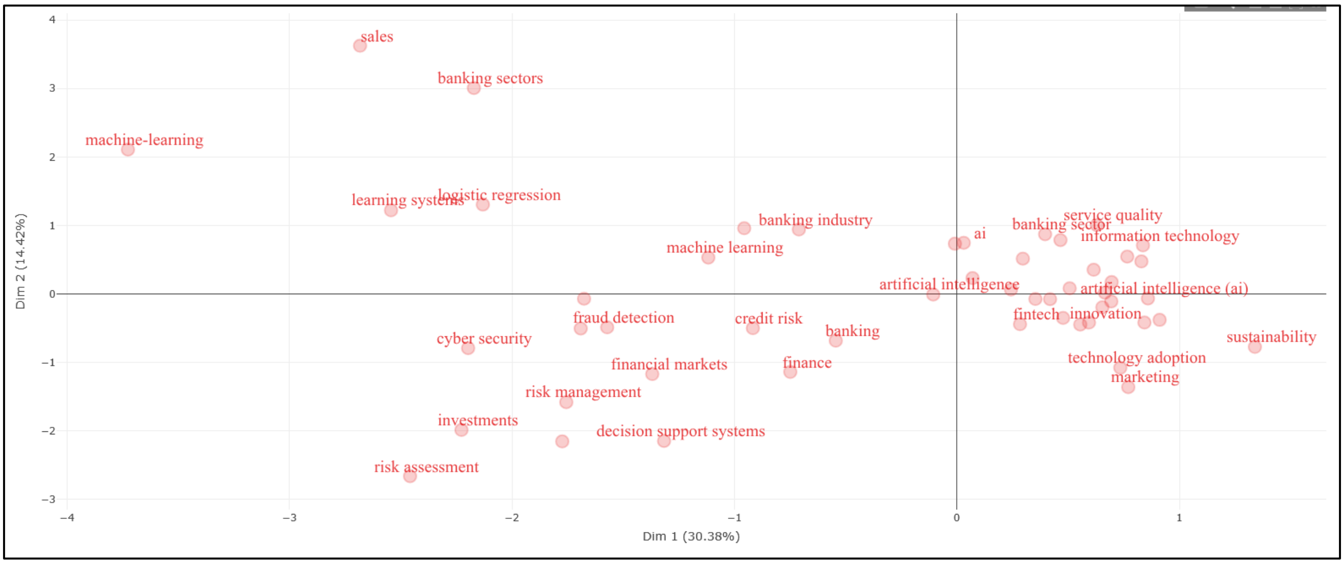
Cluster 2: Risk and Decision Making – the cluster focuses on the risk and financial analytics research with strong used of decision modelling. The keyword likes credit risk, financial market, decision support system, fraud detection, risk management and investment highlights traditional but still highly relevant themes reflecting the backbone of banking research.

Cluster 3: Statistical Modelling techniques- the cluster focuses on statistical modelling techniques like logistic regression, decision trees, and time-series models within AI to analyse large banking datasets showing declining dominance and providing theoretical ground for new AI models that helps in fraud detection, credit scoring, risk management, and improving customer decision-making.

Cluster 4: Cyber security and risk assessment- The cluster represents important variables affecting banking performance. AI techniques help detect vulnerabilities, prevent fraud, and improve overall system security.

Cluster 5: Marketing and Technology Adoption- Adoption of digital tools and AI enhances customer experience and drives efficient credit and financial services.

Figure 10: Factor analysis



Note: Author's Elaboration

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Source: Scopus

Studies have suggested that trust case of use have made significant influence in the adoption of AI- driven banking. A paradigm shift from basic to AI driven analytics, followed by interaction with sustainability and currently emerging tools like AI and risk management, cyber security in AI driven banks, AI in finance and declining themes such as traditional credit assessment, logistic regression, sales, banking sectors and legacy processes underscore the obsolescence of manual methods in the era of intelligent banking solutions.

4 Conclusion and Recommendations

This study offers a detailed bibliometric analysis that presents an overview of the research landscape concerning the uses of AI in the banking sector. Our findings underscore the considerable focus academia has placed on this subject, highlighting the substantial academic interest it has attracted. Comprehending the dynamic trends and patterns in the literature is essential for acquiring important insights into the achievements, obstacles, and prospects of this continuously expanding field. RQ1 and RQ2 examine publication patterns, average citation trends, cumulative yearly growth rates, leading authors, and the most important authors, highlighting a significant increase in publications concerning AI-driven applications in the banking sector over the previous decade. RQ3 and RQ4 rigorously analyse the topic structure and conduct factor analysis, facilitating the classification of the extensive literature into five distinct clusters. Moreover, it delineates significant research deficiencies that present advantageous prospects for forthcoming academic endeavours and policymakers.

Comprehensive academic research has revealed numerous advantages and obstacles in fields including digital finance, cybersecurity, innovation, sustainability, and the utilization of AI methodologies in risk management and forecasting. These innovations have enabled banking institutions to get enhanced insights and proficiently manage risks. Nonetheless, ethical concerns around AI and data protection issues endure, highlighting the necessity for additional research to guide best practices in the banking sector. The banking sector has experienced substantial changes due to the implementation of AI-driven methodologies. As technology progresses, we may expect greater improvements in AI applications that will propel advancements in the banking sector.

Thematic advancements indicate a shift from basic fields like as algorithmic trading and machine learning to sustainability-focused sectors like green finance, mirroring global efforts to match financial technologies with ethical banking goals. Concerns over data privacy stem from the increasing utilization of personal and financial information, while algorithmic bias presents threats to fair access in banking services. Resolving these concerns necessitates robust interdisciplinary and international collaboration, amalgamating knowledge in AI-driven technology, ethics, and finance. Future research must emphasize inclusivity, sustainability, and explainable AI to address these concerns and foster equitable growth in the banking sector. The bibliometric results underscore the disruptive impact of AI on banking services, with advancements in machine learning, natural language processing, and predictive analytics instigating substantial change.

However, a rapid pace of development highlights urgent issues with inclusion, ethics, and regulations, highlighting the necessity of adopting AI in a balanced manner. This analysis reveals robust publication growth through 2030, followed by stagnation, indicating market saturation, diminishing returns on new contributions, and potential shifts toward quality over quantity amid global academic pressures like reviewer fatigue. Future efforts should prioritize impactful, interdisciplinary work to reinvigorate the field rather than volume expansion. In conclusion, while AI adoption in banking is advancing and core applications like credit risk and fraud detection are well-established, there is a clear need for further research on emerging themes such as ethical AI, sustainability, and trust dynamics. Addressing these gaps will help ensure that AI in banking not only improves technical performance but also strengthens customer trust, regulatory compliance, and responsible adoption in real-world banking environments.

The present contribution is not free from limitations. First of all, the study reliance on publications indexed exclusively in Scopus, which may exclude valuable contributions available in other databases such as Web of Science, PubMed, or Google Scholar. These constraints suggest that future research should draw on a wider range of sources and regularly update findings to keep pace with the rapid developments in this field. Alternative analytical software could also be employed to generate further insights. Another limitation stems from the exclusive focus on published academic literature, which may underrepresent industry-driven innovations and informal financial practices. The bibliometric approach captures measurable scholarly output but may overlook policy documents, technical standards, and other forms of literature. Moreover, the sharp decline observed in 2026 data likely reflects incomplete publication cycles rather than a genuine reduction in research activity. To achieve a more comprehensive evaluation, future studies should integrate qualitative methods, integration of other machine learning approaches or other econometric tools and primary data collection alongside bibliometric analysis.

Despite the limitations revealed in the contribution, the study has made several theoretical and practical implications. The result from the research shows the significance and transformative role of AI in financial technology, innovation, sustainability and, further investigation is required into issues such as AI driven technology adoption, fraud detection, data privacy. As sustainability ascends to global significance, research must investigate how AI-driven banking may facilitate environmental objectives through initiatives such as green financing and sustainable investment frameworks. The integration of AI with banking poses intricates regulatory problems, especially in protecting customer trust, preserving financial stability, and guaranteeing cybersecurity. The increasing dependence on AI-driven banking solutions necessitates a thorough examination of sophisticated risk management tactics, especially those focused on cyber threats and fraud detection. Policymakers and scholars must prioritize ethical AI considerations and data privacy issues stemming from the swift adoption of AI, while ongoing efforts to enhance technological literacy and infrastructure in rural areas are crucial to optimize the advantages of AI-enabled banking and financial services. Subsequent future research in AI and banking may investigate qualitative methodologies to comprehend adoption obstacles and ethical issues, employing econometric instruments to examine Scopus data for enhanced insights.

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