



Review

Artificial Intelligence in Banking Risk Management: A Bibliometric Analysis

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Abstract

Artificial intelligence (AI) is increasingly embedded in banking risk management, yet academic research on this topic remains conceptually fragmented and dispersed across multiple disciplines. This study examines global publication trends and thematic structures related to AI applications in banking risk management through a bibliometric analysis of 83 peer-reviewed articles indexed in the Web of Science Core Collection for the period 2020–2024. The analysis was conducted using Bibliometrix (R-package, version 4.1), its web interface Biblioshiny (2024 release), to evaluate publication dynamics, citation performance, authorship patterns, and thematic clusters. Results show a substantial rise in scientific interest, with annual publication growth of 41.4% and international co-authorship reaching 30%. Five major thematic clusters were identified, including AI-enabled credit risk assessment, fraud detection, operational and cyber-risk mitigation, FinTech adoption, and regulatory compliance. Approximately 30% of the articles appeared in the top ten journals publishing on the topic, and the dataset recorded more than 3800 cited references. The findings indicate that AI contributes to enhanced predictive accuracy, real-time anomaly detection, and supervisory efficiency in banking risk management, while persistent challenges relate to model transparency, data quality, and regulatory adaptation. This study offers a systematic, data-driven understanding of the intellectual landscape and research evolution of AI-driven banking risk management from 2020 to 2024.

Keywords: artificial intelligence; banking; risk management; bibliometrics; fintech; credit risk; machine learning; information and communication technologies

1. Introduction

The rapid digitalization of financial services and the widespread adoption of data-driven technologies have transformed the way banks identify, assess, and mitigate risks. Artificial intelligence (AI), encompassing machine learning, natural language processing, and advanced analytics, has become one of the most influential technological drivers reshaping modern banking operations. As the financial sector becomes increasingly complex and interconnected, banks face heightened exposure to credit, operational, cyber, liquidity, and compliance risks, prompting a growing reliance on AI-enabled tools to enhance predictive accuracy, strengthen surveillance mechanisms, and support real-time decision-making. These developments underscore the rising relevance of AI as a strategic component of risk management frameworks in global banking systems.

Despite rapid technological progress, the integration of AI into risk management remains uneven and raises new conceptual, regulatory, and operational challenges. The



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opacity of AI models complicates supervisory oversight, while issues such as data quality, model bias, algorithmic governance, and compliance with evolving regulatory standards pose additional constraints. Moreover, the proliferation of AI-based solutions has led to a dispersed body of academic work spanning finance, computer science, information systems, and management studies. This fragmentation limits the ability of scholars and practitioners to form a comprehensive and coherent understanding of how AI is being used to support risk management functions across banking institutions. As a result, a clear scientific problem emerges, although research on AI in banking has expanded significantly in recent years, there is no integrated mapping of the intellectual landscape, thematic evolution, and collaboration patterns that shape this interdisciplinary field. Without such synthesis, it remains difficult to identify dominant research areas, conceptual gaps, and emerging directions relevant to both academic inquiry and practical risk management. Addressing this problem requires a systematic, data-driven approach capable of consolidating dispersed knowledge and revealing the structural dynamics of literature.

In recent years, there has been a significant increase in the utilization of artificial intelligence (AI) in banking, fundamentally transforming the methods by which financial institutions evaluate and mitigate risks. AI systems can provide improved prediction precision for credit, market, and operational risks; yet, they also add novel uncertainties. So far, no bibliometric study has thoroughly delineated the application of AI in banking risk management. Current bibliometric evaluations have analyzed digital finance and FinTech in general, as well as AI in finance, although they do not specifically address banking risk. Brika (2022) performed a bibliometric analysis of FinTech trends and digital finance utilizing ScienceDirect data from 2006 to 2020, discovering clusters including blockchain, digital lending, and inclusion. Roy et al. (2025) conducted a thematic mapping analysis of 607 Web of Science (WoS) papers on artificial intelligence and finance, encompassing topics such as risk management and market efficiency. Recent studies have examined rising vulnerabilities in fintech-driven banking systems, particularly in emerging economies such as China and India. (Recent studies have examined rising vulnerabilities in fintech-driven banking systems, particularly in emerging economies such as China and India). These significant publications, however, do not explicitly address AI applications in traditional banking risk management, resulting in a deficiency in comprehension about AI's influence on risk procedures in banks.

This research presents three novel contributions to the literature about artificial intelligence in banking risk management. Initially, it offers a risk-specific bibliometric analysis of AI research by distinctly categorizing credit, fraud, operational, cyber, and compliance-related concerns, rather than considering risk management as a mere ancillary aspect of FinTech or digital finance. Secondly, it emphasizes the post-2020 timeframe (2020–2024), documenting fundamental transformations in research agendas resulting from intensified digitalization, regulatory constraints, and the advancement of machine learning methodologies in banking. Third, the research correlates bibliometric clusters with real banking risk functions, thus connecting abstract scientometric patterns to applicable risk management practices. This study addresses the demand for better-organized and policy-relevant syntheses of AI-driven financial research.

From a theoretical perspective, the adoption of artificial intelligence in banking risk management can be explained through information asymmetry theory, risk management theory, and technology adoption frameworks. Information asymmetry theory suggests that enhanced data-processing capabilities reduce adverse selection and moral hazard, particularly in credit and fraud-related risks. Risk management theory emphasizes the role of advanced quantitative models in identifying, measuring, and mitigating financial risks under uncertainty. Technology adoption and diffusion theories further explain

how banks integrate AI tools based on perceived usefulness, regulatory pressure, and organizational readiness.

Although these theoretical perspectives provide a strong foundation, existing empirical and review-based studies remain fragmented. Prior research either focuses on individual AI techniques, isolated banking risk categories, or broad FinTech ecosystems without systematically linking observed research patterns to underlying theoretical mechanisms. Consequently, there is limited understanding of how AI-driven banking risk management research has evolved structurally and thematically in response to theoretical, regulatory, and technological forces.

To address this gap, this study applies a theory-informed bibliometric approach to map the intellectual structure, thematic evolution, and collaboration patterns of AI research in banking risk management from 2020 to 2024. By explicitly linking bibliometric clusters to established theories and banking risk categories, the study advances existing literature beyond descriptive mapping and provides a structured analytical contribution.

Consistent with the descriptive nature of bibliometric studies, the present research does not aim to test causal hypotheses but rather to identify structural patterns and thematic developments in the literature.

2. Theoretical Background, Literature Review and Analytical Expectations

2.1. Theoretical Foundations of Artificial Intelligence in Banking Risk Management

The growing adoption of artificial intelligence (AI) in banking risk management can be interpreted through several well-established theoretical perspectives widely applied in finance, risk management, and information systems research. These perspectives include information asymmetry theory, modern risk management theory, and technology adoption frameworks, each of which provides a conceptual explanation for the increasing reliance on data-driven analytical tools in financial institutions.

First, information asymmetry theory explains how unequal access to information between financial institutions and borrowers generates problems such as adverse selection and moral hazard (Akerlof, 1970; Stiglitz & Weiss, 1981). In banking, information asymmetry is particularly relevant in credit markets, where lenders often lack complete information about borrower quality and risk profiles. Artificial intelligence and machine-learning techniques can significantly reduce such asymmetries by processing large volumes of structured and unstructured financial data, enabling more accurate borrower assessment and credit scoring (Berg et al., 2020; Fuster et al., 2022). Fernández-Arias et al. (2018) demonstrate the effectiveness of advanced classification models in predicting financial soundness in banking systems, highlighting the importance of data-driven approaches in risk assessment. Spankulova et al. (2024) demonstrate that ICT infrastructure and cultural accessibility significantly influence economic development, highlighting the importance of digital readiness and institutional conditions for the effective adoption of advanced technologies such as artificial intelligence. Empirical evidence suggests that AI-driven models improve predictive accuracy and reduce credit misclassification compared to traditional statistical approaches, thereby mitigating information inefficiencies in financial intermediation.

Second, risk management theory emphasizes the systematic identification, measurement, and mitigation of financial risks through analytical models and quantitative techniques (Jorion, 2007; Hull, 2018). Rolando and Mulyono (2024) examine the application of artificial intelligence in FinTech risk management, identifying key challenges related to model reliability, regulatory compliance, and the integration of AI-driven risk assessment tools. Traditional risk management frameworks rely on econometric models and predefined assumptions regarding risk distributions and correlations. However, the increasing com-

plexity of financial systems has encouraged the adoption of AI-based approaches capable of capturing nonlinear relationships and dynamic patterns in financial data (Khandani et al., 2010; Heaton et al., 2017). Fountaine et al. (2019) emphasize that successful AI adoption in organizations depends not only on technology but also on organizational culture, governance, and strategic alignment. Adeniran et al. (2024) emphasize the importance of strategic risk management in financial institutions, highlighting the role of regulatory compliance and structured risk governance frameworks in enhancing financial stability. Machine learning algorithms, deep learning models, and anomaly detection systems enable banks to detect emerging risks, forecast default probabilities, and monitor operational vulnerabilities in real time (Davenport & Ronanki, 2018; Ahmed et al., 2023). This is supported by Fares et al. (2022), who systematically review the literature on AI in banking and identify key application areas, including risk assessment and financial monitoring. As a result, AI expands the analytical capabilities available to financial institutions for managing credit risk, operational risk, cyber risk, and regulatory compliance.

Third, technology adoption and innovation diffusion theories explain how organizations adopt new technologies based on perceived usefulness, institutional pressures, and organizational readiness (Davis, 1989; Rogers, 2003). In financial institutions, technology adoption is influenced not only by operational efficiency considerations but also by regulatory requirements, competitive pressures, and digital transformation strategies (Venkatesh et al., 2003; Fountaine et al., 2019). The adoption of AI technologies in banking therefore reflects a broader process of digital innovation in financial services, where banks integrate advanced analytics to enhance decision-making, risk monitoring, and compliance processes.

Taken together, these theoretical perspectives suggest that the increasing use of artificial intelligence in banking risk management is driven by both information efficiency gains and institutional pressures for technological innovation. Consequently, these theories provide an appropriate conceptual foundation for examining how academic research on AI-driven banking risk management has evolved in response to technological change, regulatory developments, and the growing availability of financial data.

2.2. Empirical Studies on AI Applications in Banking Risk Management

Building on these theoretical foundations, a rapidly expanding body of empirical research has examined AI applications across various banking functions and risk categories. Research on artificial intelligence and its applications in banking risk management has expanded significantly over the last decade, reflecting the financial sector's increasing reliance on data-driven technologies to strengthen risk assessment, regulatory compliance, and operational resilience. However, despite accelerated technological change, academic work remains fragmented across multiple disciplinary domains, including finance, information systems, computer science, organizational studies, and regulatory sciences. Bahoo et al. (2020) further emphasize the broader transformation of financial systems driven by technological innovation and data-driven approaches. Safari et al. (2020) analyze user attitudes and behavioral intentions toward internet banking in developing financial systems, highlighting the importance of trust, perceived usefulness, and technological readiness in the adoption of digital financial services. Zhang et al. (2020) examine the impact of artificial intelligence and blockchain technologies on the accounting profession, demonstrating how advanced digital technologies transform financial processes, data management, and decision-making frameworks.

A substantial share of empirical studies focuses on credit risk assessment, demonstrating that machine learning and deep learning models outperform traditional statistical techniques in default prediction and borrower classification. Studies such as Brown (2024),

Adepetun et al. (2022), and Mhlanga (2021) highlight the growing use of AI in credit scoring, financial inclusion, and lending decisions. Achary (2021) highlights the transformative role of artificial intelligence in the banking sector, particularly in improving operational efficiency, customer service, and risk management practices. Alassuli (2025) examines the impact of artificial intelligence and robotic process automation on internal audit efficiency in commercial banks, demonstrating how AI-driven systems can enhance operational control and risk management processes. Bouchetara et al. (2024) analyze the application of artificial intelligence in financial risk management, emphasizing its role in improving decision-making, risk assessment, and regulatory compliance in financial systems. These findings are consistent with information asymmetry theory, as AI-based models improve information processing and borrower evaluation.

Another prominent stream of research addresses fraud detection and financial crime prevention, including anti-money laundering (AML). Research by Ngai et al. (2011), Hassan et al. (2023), and Javaid et al. (2022) demonstrates how AI-enabled anomaly detection and transaction monitoring systems enhance banks' ability to identify suspicious activities in real time. This literature underscores the relevance of AI for operational risk mitigation and regulatory compliance.

Beyond credit and fraud-related risks, several studies examine AI's role in operational and cyber risk management. Zhan et al. (2024), Nourallah (2023), and Sang (2024) explore AI-driven approaches to cybersecurity, system resilience, and operational disruption management. A. Kumar et al. (2022) characterize the emergence of Banking 4.0 as a paradigm shift driven by artificial intelligence, highlighting its role in transforming financial services, enhancing automation, and improving risk management processes. These studies indicate that AI contributes to early warning systems and enhances banks' capacity to respond to complex and rapidly evolving threats.

In parallel, a growing number of studies adopt a conceptual or normative perspective, focusing on challenges associated with AI adoption in banking. Zhang et al. (2020) and Brynjolfsson and McAfee (2014) emphasize issues related to model opacity, algorithmic bias, governance, and regulatory uncertainty. Othman (2025) examines AI and FinTech adoption in the banking sector, emphasizing the importance of institutional, cultural, and regulatory factors in shaping the implementation of AI-driven financial innovations. These concerns are increasingly reflected in discussions of explainable AI, ethical AI, and supervisory technology.

Alongside application-oriented research, an important body of literature applies bibliometric and scientometric methods to analyze structural patterns in digital finance and FinTech research. Jafri et al. (2025) conduct a bibliometric analysis of FinTech research using Scopus-indexed publications, identifying dominant themes such as digital banking, financial innovation, and technology-driven risk management, as well as emerging research directions in AI-based financial services. Studies by Bhatt et al. (2022), Zou et al. (2023), Paltrinieri et al. (2023), and Gangwar et al. (2025) demonstrate the usefulness of bibliometric approaches for mapping thematic clusters, intellectual structures, and research evolution. Nnaomah et al. (2024) provide a comparative analysis of AI applications in banking risk management across different national contexts, highlighting variations in regulatory environments and the adoption of AI-driven risk assessment tools. This trend is also supported by bibliometric studies exploring the relationship between FinTech and sustainability in financial markets (Gupta et al., 2023). However, these studies typically focus on FinTech, digital finance, or financial innovation broadly, rather than on banking risk management as a distinct analytical domain.

2.3. Research Gaps

Despite the rapid expansion of research on artificial intelligence in finance, several important gaps remain in the existing literature.

First, many studies focus on specific AI techniques or isolated applications, such as credit scoring or fraud detection, without systematically examining how these technologies affect different categories of banking risk. Consequently, the relative emphasis placed on various banking risk types—such as credit risk, operational risk, cyber risk, and compliance risk—remains unclear.

Second, existing bibliometric studies primarily examine FinTech and digital finance research in general, rather than focusing specifically on AI applications in banking risk management. As a result, the intellectual structure and thematic evolution of AI-driven risk management research remain insufficiently mapped.

Third, the literature often lacks explicit theoretical integration, with many studies emphasizing algorithmic performance while paying limited attention to the theoretical mechanisms explaining AI adoption and its implications for risk management practices.

Fourth, much of the existing bibliometric research focuses on earlier periods of digital finance development and does not fully capture the post-2020 expansion of AI applications in banking, which has been accelerated by rapid digitalization, regulatory reforms, and advances in machine learning technologies.

These limitations indicate the need for a theory-informed bibliometric analysis that systematically maps the intellectual structure of AI research in banking risk management and identifies the dominant themes shaping this emerging field.

2.4. Analytical Expectations

Based on the theoretical foundations and research gaps identified above, this study formulates several analytical expectations concerning the thematic and structural characteristics of research on artificial intelligence in banking risk management. These hypotheses are derived from information asymmetry theory, risk management theory, and technology adoption frameworks.

Expectation 1: Thematic concentration of AI research in banking risk management.

Information asymmetry theory suggests that financial institutions invest heavily in technologies capable of improving information processing and borrower evaluation (Akerlof, 1970; Stiglitz & Weiss, 1981). In the context of banking, the most prominent areas affected by information asymmetry include credit risk assessment and fraud detection, where lenders and regulators must process large volumes of financial and transactional data. Artificial intelligence technologies have demonstrated strong capabilities in predictive modeling and anomaly detection, making them particularly valuable for these applications (Khandani et al., 2010; Berg et al., 2020). Ellili (2022) further contributes to this stream of research by providing a bibliometric and content analysis of FinTech, highlighting the increasing role of sustainability and innovation in financial services.

Consequently, academic research is expected to concentrate on these domains because they represent the areas where AI provides the most immediate operational benefits for financial institutions.

Analytical Expectation 1: Based on the existing literature on artificial intelligence in finance, research on AI in banking risk management is expected to concentrate primarily on credit risk assessment and fraud detection.

Expectation 2: Methodological evolution toward advanced AI techniques.

Technology adoption and innovation diffusion theories suggest that as technologies mature, research and practical applications shift toward more sophisticated analytical approaches (Rogers, 2003; Venkatesh et al., 2003). In the financial sector, recent advances in

computational capacity and data availability have enabled the increasing use of machine learning, deep learning, and advanced analytics for risk modeling (Heaton et al., 2017).

Traditional risk management models typically rely on econometric methods such as logistic regression or time-series forecasting. However, modern AI-based methods can capture nonlinear relationships and complex data structures, which are common in financial risk environments (Davenport & Ronanki, 2018). As a result, academic research is expected to increasingly adopt advanced AI methodologies.

Analytical Expectation 2: Research on AI in banking risk management is expected to increasingly employ advanced analytical techniques such as machine learning and deep learning.

Expectation 3: Structural concentration of knowledge production.

Bibliometric studies in emerging research domains frequently reveal that knowledge production is concentrated in a relatively small number of journals, countries, and research institutions (Zupic & Čater, 2015). This phenomenon reflects differences in research funding, technological capabilities, and institutional expertise.

Given that AI research requires specialized technical skills and access to large datasets, it is likely that a limited number of countries and academic institutions dominate research output in this field. In addition, interdisciplinary research topics often concentrate in specific journals that specialize in financial innovation and digital finance.

Analytical Expectation 3: The academic literature on AI-driven banking risk management is expected to show structural concentration in a limited number of journals, institutions, and countries.

3. Methodology

This study employs a structured bibliometric methodology to analyze scientific publications on artificial intelligence (AI) in banking risk management. Bibliometric analysis is appropriate because it allows for a systematic evaluation of publication trends, intellectual linkages, and thematic structures in research fields characterized by rapid development and interdisciplinary contributions. The procedure combines transparent database selection, carefully designed search criteria, multi-stage screening, and the use of specialized software for quantitative and qualitative analysis.

Given the descriptive nature of bibliometric analysis, the study does not aim to test causal relationships. Instead, several analytical expectations are formulated to guide the interpretation of the bibliometric results and identify dominant research patterns in the literature. The bibliometric analysis was conducted using the Bibliometrix R-package, a widely recognized tool for science mapping and performance analysis (Aria & Cuccurullo, 2017). Waltman and van Eck (2019) discuss the importance of field normalization in scientometric analysis, emphasizing its role in ensuring comparability of citation-based indicators across different research domains.

We chose WoS because it indexes high-quality journals and provides robust citation data. Scopus covers a larger number of titles (approximately 31% more journals than WoS) and more conference proceedings, but previous comparisons show that WoS covers the majority of citations found in Scopus (e.g., Scopus includes 93% of WoS citations). Thus, WoS is a standard choice for bibliometric reviews, and using it enhances comparability with prior studies (e.g., Roy et al., 2025). We acknowledge that excluding IEEE Xplore, Scopus, and grey literature may bias results towards academic journals, but this was necessary given resource constraints. The significant overlap in core content between WoS and Scopus suggests that our corpus still represents the central scholarly work on AI in finance.

The Web of Science (WoS) Core Collection was chosen as the exclusive data source due to its high indexing standards, comprehensive citation metadata, and wide use in

bibliometric research. WoS supports the construction of co-citation, co-authorship, and bibliographic coupling networks, which are essential for mapping the intellectual and social structure of a research field.

Because AI-related work in banking is highly dispersed, a broad and inclusive search strategy was adopted. Narrow expressions such as “risk management” do not always appear explicitly in titles or abstracts, even when the study clearly relates to risk. Therefore, the primary search term was the keyword “artificial intelligence”, combined with WoS subject categories related to finance and banking in order to capture all potentially relevant documents. The search was conducted on 31 December 2024. All document types and years were initially allowed to avoid premature exclusions at the search stage. Initial search outcome: the WoS query returned 644 documents related to artificial intelligence in the broader financial and economic context. This large initial pool reflects the popularity of AI applications in finance and business but includes many studies outside banking and/or without a risk-management focus (Figure 1).

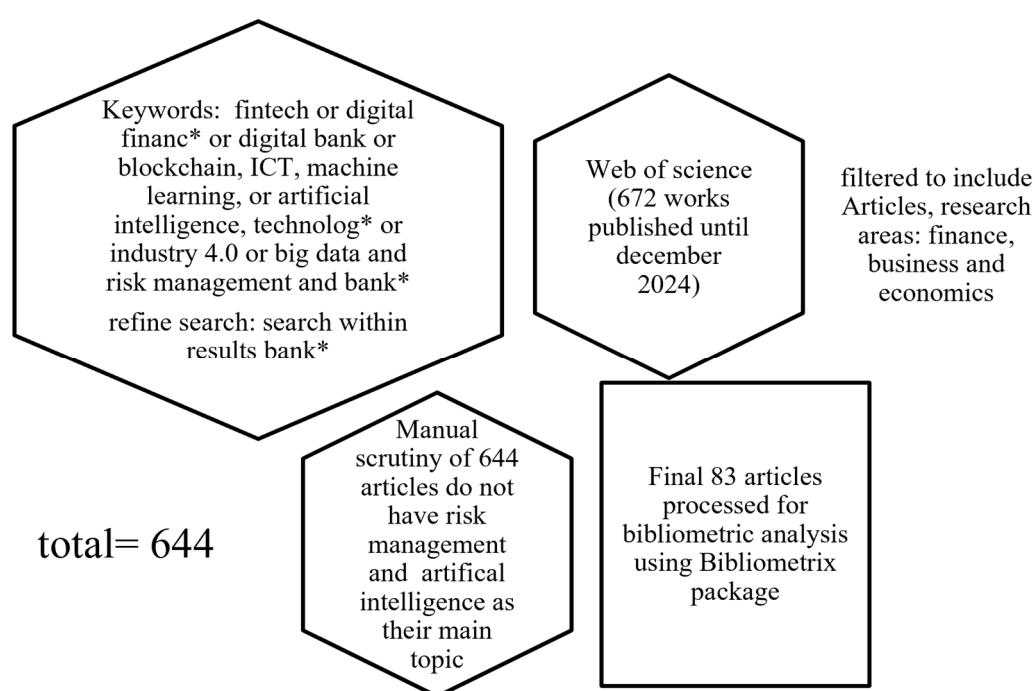


Figure 1. Process Flowchart. Note: * indicates key stages in the screening and selection process.

Data Screening

A multi-stage screening protocol was applied to refine the initial 644 documents and isolate publications that directly address AI in banking risk management. The screening consisted of three main stages.

Stage 1 includes Duplicate Removal and Initial Filtering process. Duplicate records and clearly irrelevant items were removed first. At this stage, documents focusing on AI in non-financial sectors (e.g., healthcare, education, manufacturing) were excluded. Many papers addressed AI in general business analytics, information systems, or macroeconomic forecasting without reference to banking institutions. These were also removed.

Stage 2 includes Title–Abstract–Keyword Screening process. The remaining documents were then evaluated based on their titles, abstracts, and author keywords. Two researchers independently screened each record, and any disagreement was resolved through discussion. Publications were excluded if they did not involve banks or banking institutions; focused on general FinTech or digital finance without a risk-related component; discussed AI in banking operations (e.g., marketing, customer experience) without any

explicit link to risk, prudential issues, or regulatory compliance; or examined risk management but did not involve AI, machine learning, or related techniques. This stage eliminated a substantial portion of general AI-in-finance studies and ensured that only documents with a clear connection to banking risk were retained.

Stage 3 includes the Full-Text Assessment process. For ambiguous cases where relevance could not be determined from the title and abstract alone, full texts were consulted. Papers were excluded if AI or risk was mentioned only briefly or if the discussion of banking risk management was superficial and not central to the study's objectives, methods, or findings. After completing all stages of screening and eligibility checking, the dataset was reduced from 644 initial records to a final set of 83 publications that directly examine artificial intelligence in banking risk management. This sharp reduction underlines how widely AI is discussed in finance in general, but also how limited the core body of work is when strict criteria for both banking and risk management are applied.

To assess the robustness of the findings, sensitivity checks were conducted by varying keyword inclusion thresholds and minimum citation cut-offs. The core thematic clusters and dominant research streams remained stable across specifications, indicating that the results are not driven by arbitrary parameter choices.

To document the procedure clearly and ensure replicability, the main stages of the literature search and screening process are summarized in Table 1.

Table 1. The literature search and selection process.

Filters/Actions Applied	Result
Data Collection	
Database	Web of Science Core Collection
Search fields	Title, abstract, author keywords, Keywords Plus
Search keywords/strategy	"Artificial intelligence" (primary) combined with finance and banking subject categories
Initial output	644 documents retrieved
Data Screening	
Scope filtering	Excluded non-financial and non-banking AI studies
Title–abstract–keyword review	Excluded general AI or FinTech papers without risk focus; excluded risk papers without AI
Full-text verification (ambiguous cases)	Removed documents where AI or risk was only marginally mentioned
Final Dataset	
Indexing and metadata validation	All retained publications are WoS-indexed and bibliographically complete
Final sample for bibliometric analysis	83 publications
Bibliometric Analysis	
Tools	Bibliometrics and Biblioshiny App, Microsoft Excel

The bibliometric analysis proceeded in four main steps: (1) Descriptive analysis of publication trends, sources, authorship, and citations; (2) Keyword co-occurrence analysis to identify dominant topics and emerging themes; (3) Thematic and conceptual structure analysis to classify themes as motor, basic, niche, or emerging; (4) Intellectual and social structure analysis through co-citation, bibliographic coupling, and co-authorship networks (Ashurbayli-Huseynova & Garmidarova, 2025).

To complement the quantitative mapping, a qualitative content analysis was performed. Abstracts and selected full texts were read to interpret thematic clusters, refine

the labels given to each cluster, and better understand how AI techniques are applied to different categories of banking risk (credit, operational, fraud, compliance, etc.). This mixed approach allows the statistical patterns revealed by bibliometrics to be linked to substantive insights from literature (Zupic & Čater, 2015).

By combining a broad initial search, rigorous multi-stage screening, established bibliometric tools, and a qualitative interpretive layer, the methodology ensures that the final sample of 83 publications provides a focused and reliable representation of the scientific landscape on AI in banking risk management over the period 2020–2024.

The study used several tools for Web of Science data analysis: Bibliometrix (R-package, version 4.1) and its web interface Biblioshiny (2024 release)—for descriptive statistics (annual scientific production, authorship, journals, citations), thematic mapping, Microsoft Excel—for initial data cleaning and keyword harmonization (e.g., unifying variants such as “machine learning” and “ML”).

4. Results

This section presents the empirical findings of the bibliometric analysis of publications addressing artificial intelligence (AI) applications in banking risk management. The analysis is based on 83 peer-reviewed articles indexed in the Web of Science Core Collection for the period 2020–2024. The results are organized into four subsections: (1) publication trends and research productivity, (2) country and institutional contributions, (3) influential authors, journals, and documents, and (4) conceptual, intellectual, and social structures derived from keyword co-occurrence, co-citation, bibliographic coupling, and co-authorship networks.

Table 2 presents the main descriptive statistics of the dataset used in this study. The analysis covers the period from 2020 to 2024 and includes 83 documents published across 42 sources, such as journals and books. The dataset demonstrates a strong research expansion, with an annual growth rate of 41.42%, while the average age of documents is 1.26 years, indicating the recent and rapidly evolving nature of the research field. On average, each document received 9.28 citations, resulting in a total of 3818 cited references. In terms of content characteristics, the dataset includes 191 Plus keywords and 221 author keywords, reflecting thematic diversity. Authorship analysis shows contributions from 175 authors, with an average of 3.66 co-authors per document and 30% international co-authorship, highlighting a moderate level of global research collaboration (see Table 2).

Table 2. Main descriptive indicators of the dataset (Bibliometrix output).

Main Information About Data	Value
Timespan	2020:2024
Sources (books, journals, etc.)	42
Documents	83
The percentage of annual growth	41.42
Average Age of Documents	1.26
Citations per document on average	9.28
Citations (references)	3818
Document contents	
Plus keywords (ID)	191
Keywords of the Author (DE)	221
Authors	175
Single-authored document authors	5
Collaboration of authors	
Co-authors per document	3.66
Percentage of international co-authorships	30

Approximately 30% of all documents appeared in the top ten most active journals, indicating a moderately concentrated yet interdisciplinary literature. Journals such as *Journal of Financial Services Marketing* and *International Journal of Bank Marketing* emerged as particularly productive sources. At the same time, the dispersion across 42 journals demonstrates that the topic attracts attention from finance, management, computer science, information systems, and operations research communities.

Descriptive indicators from Bibliometrix reveal that the 83 articles collectively cite 3818 references and include 191 Keywords Plus terms and 221 author keywords. The average number of authors per paper is 3.66, with only five single-authored publications, indicating a strong tendency toward collaborative research. International co-authorship stands at 30%, suggesting an emerging but globally distributed research community.

The global distribution of publications highlights a diverse authorship structure. Although specific country rankings are not listed in the extracted data, institutional collaboration patterns, reflected in the 30% international co-authorship rate, indicate that AI in banking risk management has become a subject of transnational academic cooperation. The involvement of institutions from both developed and emerging economies reflects the universal relevance of AI-driven risk tools in banking systems undergoing digital transformation.

Institutions publishing in this area include research centers focused on finance, computer science, information systems, and engineering, illustrating the inherently interdisciplinary nature of the field.

The high average number of authors per paper and low single-authorship rate signal that research in this area is typically collaborative, likely due to its interdisciplinary requirements (combining expertise in finance, data science, etc.). The collaboration index in our sample is indeed very high—over 95% of the papers are co-authored by two or more researchers. Most of the scientific papers on AI in banking risk management are contributed by authors from leading countries such as the United Kingdom, China, India, the United States, and Indonesia (Figure 2). Countries with high levels of both domestic and international collaboration include China, India, and Italy (indicated by a strong presence of both single-country publications (SCP) and multiple-country publications (MCP) (Figure 3). The analysis identified a set of core journals that are frequently published on AI in banking and risk. According to Bradford's Law, approximately one-third of the articles appeared in a handful of journals. Besides the two journals already noted (JFSM and IJBM), others in the top by volume included journals in financial technology and risk management domains. This suggests that, although the topic is interdisciplinary, finance-oriented journals have thus far absorbed a significant portion of the research output.

The study also examined author productivity and influence. A total of 175 authors contributed to the corpus, but only a few authors had multiple publications on the topic, suggesting that research on AI in banking risk is still distributed without a clear dominating author or research group yet. The most prolific authors (with two or more publications each in the sample) collectively authored about 15% of the papers. Collaboration networks among authors show that even these prolific contributors often co-author with different colleagues across papers, reflecting a field where research teams form around specific projects rather than a single stable cluster of researchers working on all aspects.

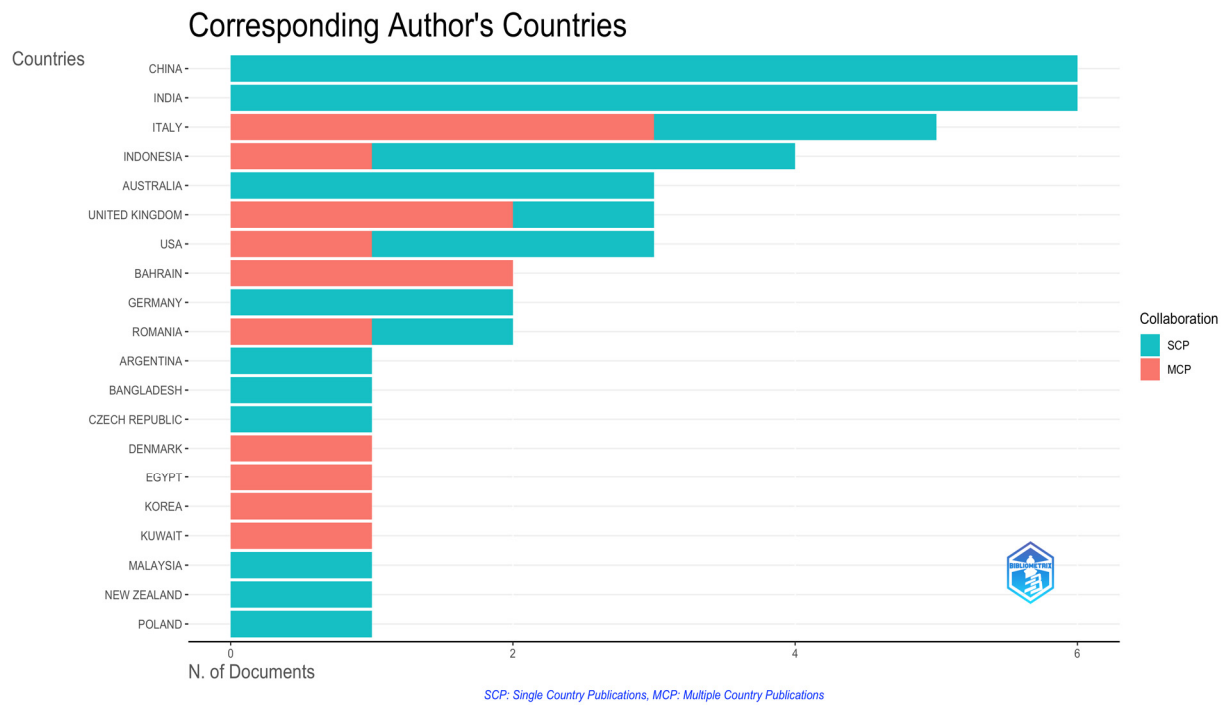


Figure 2. Top 20 Countries regarding Publication and Author Affiliation.

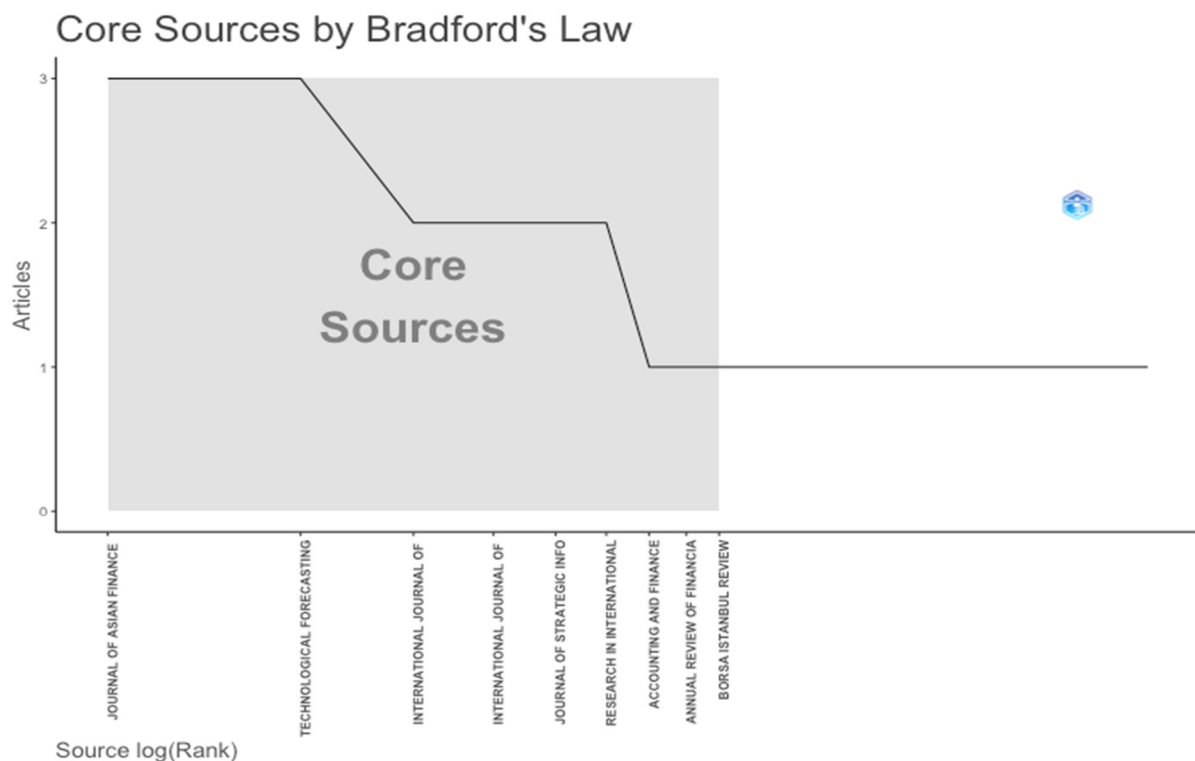


Figure 3. Top journals grouped by Bradford's Law.

Table 3 summarizes the most influential publications in the field of artificial intelligence and related applications, ranked by total citations, citations per year, and normalized citation impact. The most highly cited paper is Barbu et al. (2021) published in the Journal of Theoretical and Applied Electronic Commerce Research, which has received 83 total citations and an average of 16.60 citations per year, indicating its strong and sustained influence on the literature. S. Kumar et al. (2022) in the International Journal of Bank Marketing demonstrate high normalized citation scores, reflecting above-average impact

relative to the publication year. Overall, the results presented in Table 2 highlight the interdisciplinary nature of influential research in this domain, spanning banking, finance, marketing, economics, and technology-oriented journals. The citation structure shows that the average citation rate per article is 9.28, consistent with a relatively young yet increasingly recognized research domain. Several works that examine broader digital finance issues appear among the most influential documents (e.g., Barbu et al., 2021; S. Kumar et al., 2022; Fülöp et al., 2022). Although not all of these focus specifically on AI-based risk management, their prominence indicates that foundational concepts in digital transformation and data-driven finance underpin contemporary work on AI-enabled banking risk applications.

Table 3. Top-cited documents on AI in banking management.

Paper	DOI	Total Citations	TC per Year	Normalized TC
Barbu et al. (2021)	10.3390/jtaer16050080	83	16.60	2.86
S. Kumar et al. (2022)	10.1108/IJBM-07-2021-0351	57	14.25	4.35
Fülöp et al. (2022)	10.3846/jbem.2022.17695	29	7.25	2.22
Nguyen et al. (2022)	10.1111/eufm.12365	26	8.67	4.27
Martono et al. (2020)	10.13106/jafeb.2020.vol7.no10.1007	24	4.00	2.18
Tiwari et al. (2024)	10.1108/JFMM-11-2022-0253	15	7.50	4.83
Sánchez (2022)	10.1016/j.techfore.2022.121766	14	3.50	1.07
Fernández-Arias et al. (2018)	10.1007/s10614-017-9676-6	13	1.63	1.00
Nourallah (2023)	10.1016/j.jbusres.2022.113470	13	4.33	2.14

The relatively small corpus of publications suggests that the research field remains in an early stage of development, which is typical for emerging interdisciplinary domains identified through bibliometric analysis (Zupic & Čater, 2015; Donthu et al., 2021).

Nevertheless, citation patterns demonstrate a transition from conceptual and exploratory work toward more methodologically rigorous and empirically grounded studies, including applications of machine learning models for credit scoring, fraud detection algorithms, anomaly-based cyber-risk surveillance, and AI-supported compliance systems.

The analysis of the top-cited studies in AI and Risk management illustrates that the role of AI in finance and banking is significant and confirmed by the models and data in the top-cited papers. To understand the substance of influential studies, we conducted a structural analysis (Table 4) summarizing their themes, methods, and findings. These top-cited works cover a variety of topics: for instance, S. Kumar et al. (2022) used bibliometric methods to map bank marketing literature and discovered six thematic clusters in banking research, demonstrating the value of bibliometrics for revealing intellectual structure. Nguyen et al. (2022) discussed the symbiosis of AI, machine learning, and big data in financial technology, highlighting both the transformative potential and the ethical/regulatory issues arising from these technologies. Martono et al. (2020), although not directly related to banking, investigated technology acceptance among employees using TAM/IS success models, which is relevant to AI adoption in banks (cited by our analysis as it informs user acceptance of new systems). Sánchez (2022) provided a multi-level perspective on fintech innovation, offering frameworks that could be applied to understand AI transitions in banking. The diversity of these top papers underscores that “AI in risk management” research draws from multiple related streams, including FinTech, marketing, accounting, and organizational change.

Table 4. Structural analysis of top-cited papers.

Author	Theme	Purpose	Methods	Findings
Barbu et al. (2021)	Customer Experience in Fintech	The purpose of the study is to analyze the financial industry's customer experience (CX).	Young Romanians from Generation Z and Millennials participated in a study to evaluate customer experience in the financial industry. By computing Cronbach's α and composite reliability, construct reliability was assessed to validate the measurement model. The HTMT criterion on the conventional Fornell-Larcker criterion was used to verify discriminant validity.	All the relevant customer experience dimensions, such as cognitive, affective, and social expertise, contribute to loyalty intentions. A small contribution to the knowledge of the fintech industry's concept of customer experience. The findings indicated that in the fintech industry, consumer experience explains loyalty intentions.
S. Kumar et al. (2022)	Past, present, and future of bank marketing: a bibliometric analysis of International Journal of Bank Marketing (1983–2020)	The purpose of this study is to provide a comprehensive overview of bank marketing.	A bibliometric analysis of bank marketing literature's performance and intellectual structure	Relationship marketing and service quality, consumer behavior, customer happiness and loyalty, online or electronic banking and financial services, Islamic banking and financial services, and service failure and recovery are the six main clusters (themes) that comprise banking and financial services.
Fülöp et al. (2022)	Fintech accounting and industry 4.0: future-proofing or threats to the accounting profession?	The study looks at the current state and emerging trends of accounting digitization, as well as the responsibilities of implementation for accounting digitization.	There are a total of thirty questions based on the literature in the research model.	In the accounting industry, AI is crucial since it helps with the accountant's tasks, and blockchain technology helps the accountant oversee the activity. For accountants to embrace and use technological innovation, it must be secure and readily available.
Nguyen et al. (2022)	Big data, artificial intelligence, and machine learning: A transformative symbiosis in favour of financial technology	Artificial intelligence (AI), machine learning (ML), and big data techniques are integrated into the financial technology roadmap.	It employs descriptive analysis with several dimensions.	The framework's influence on fintech, the financial services industry, and the evolving definition of the data scientist position provides validation. There has been discussion of the negative aspects of this symbiosis, including how AI and ML techniques relate to the upcoming issues of AI ethics, regulatory technology, and intelligent data exploitation.

Table 4. Cont.

Author	Theme	Purpose	Methods	Findings
Martono et al. (2020)	Understanding the employee's intention to use information systems: Technology acceptance model and information system success model approach	Identifying the factors that influence an employee's intention to use information systems within the framework of the Information System Success Model (ISSM) and the Technology Acceptance Model(TAM)	The Warp-PLS program was utilized to do a structural equation model (SEM) analysis of data.	The results demonstrated that the employee's intention to utilize SIKEU was favorably and significantly influenced by the TAM characteristics (perceived utility and ease of use). SIKEU's practical use was significantly impacted by the ISSM dimension (information and system quality).
Sánchez (2022)	A multi-level perspective on financial technology transitions	Response to the query about how changes in financial technology take place.	Provides a multifaceted approach to the shift in financial technologies. The socio-technical landscape, regime, and niche levels are explained based on a survey of the literature.	It offers a fresh framework for financial technology transitions that may be tailored for research at the national level and utilized as an analytical tool to expound on upcoming changes in the industry.
Fernández-Arias et al. (2018)	Financial Soundness Prediction Using a Multi-classification Model: Evidence from the Current Financial Crisis in OECD Banks	Its goal is to create an early warning model that uses a one-year timeframe and separates previously rated banks (337 OECD Fitch-rated banks) into three classes according to their financial health.	Bankscope macroeconomic, regulatory, and bank-specific data are input variables used in Fitch ratings. It suggests a hybridization technique that blends the Synthetic Minority Oversampling Technique with the Extreme Learning Machine.	The suggested methodology performs better than other categorization methods already in use for predicting bank solvency. It was crucial in raising average accuracy, particularly the minority group's performance.
Nourallah (2023)	One size does not fit all: Young retail investors' initial trust in financial robo-advisors.	Its goal is to provide a theoretical framework for initial confidence in FRA and test it on YRIs in Sweden and Malaysia.	Partial least squares structural equation modeling (PLS-SEM) was used in the investigation.	The findings show that initial trust in FRAs, which motivates behavioral intention to employ the technology, is addressed by trust propensity, performance expectancy, and hedonic incentive.

The citation analysis highlights that the literature on AI in banking risk management is closely intertwined with broader FinTech and banking innovation research. Many foundational ideas and concerns (customer trust, technology adoption, strategic change, etc.) are shared across these overlapping domains.

According to the results, there are three different kinds of production: (1) static production, which occurs when all of the articles discuss a single year (Liu Y, who published six articles in 2023); (2) partially dynamic and constant production, which occurs when the articles are distributed evenly over a period of time (for instance, Kumar and Chawla, who wrote two articles annually in 2023–2024); (3) production that is both somewhat dynamic

and irregular (if the pieces are spaced out over time, as Gupta, with two articles in 2023 and two in 2024). The analysis of author productivity (Table 5) shows a few authors with multiple contributions. Chawla D. and Kumar A. each have six articles (some fractional counting due to co-authorship across papers) in our dataset. However, their citation counts per article are relatively modest, indicating their work is part of ongoing discussions rather than singular breakthrough papers. In contrast, an author like Singh S. has fewer papers (5) but very high total citations (110), suggesting one or two of those papers gained exceptional academic attention—possibly an influential review or framework. The h-index values in the table (mostly 1–3 for these authors within this niche topic) confirm that most authors are in early stages of building citation impact in this specialized field. This is expected given the recency of the topic; even prolific contributors have not yet accumulated large bodies of highly cited work specifically on AI in banking risk management.

Table 5. Top 10 most productive authors.

Authors	Articles	Articles Fractionalized	TC	C per Article	H Index	Affiliation
Chawla D (2021)	6	3	7	2.5	3	Arabian gulf univ
Kumar A (2022)	6	1.36	15	7.5	2	Amity univ
Asongu (2023)	5	2.83	4	1.5	2	Rmit univ
Joshi (2021)	5	2.5	57	19	1	Univ loyola andalucia
Jiu (2022)	5	1.53	22	7.3	1	Babes bolyai univ
Singh (2022)	5	1.75	110	18.3	1	Guizhou univ finance and econ
Ali (2021)	4	1.33	9	3	1	Shanghai lixin univ accounting and finance
Gupta (2022)	4	1.75	20	5	1	Sun yat-sen univ
Li y (2021)	4	0.92	36	5.14	1	Swinburne univ technol
Li z (2022)	4	0.83	7	3.5	3	Zhihong Lab

Note: The authors listed represent the most productive contributors identified in the dataset and do not correspond to individual cited references.

According to the results of the analysis of the Bibliometrix (R-package, version 4.1), Bradford's law, which explains how publications on a given topic are distributed among multiple magazines, was used to produce the sources (Figure 3). It is also known as the Bradford distribution, by which Samuel C. introduced the law of scattering for the first time in 1934. One interpretation holds that if journals in a subject are categorized into three categories according to the quantity of articles they produce, then the number of journals in each category will be distributed in proportion, with each group holding around one-third of all articles. Journal of Banking and Financial Services, International Journal of Bank Marketing, and Technological Forecasting and Social Change emerged among the top sources, each contributing multiple articles to our dataset.

Figure 4 further illustrates the top 10 relevant sources by volume, confirming that while no single journal dominates the field, there is a recognizable group of go-to journals for publishing AI-in-banking research.

The 10 best sources were identified by the number of scientific papers related to the keyword of choice (Figure 4). The Journal of Asian Economics and Business Finance and Technological Forecasting and Social Change published the most, six scientific papers. Furthermore, two of the best sources with the most publishing of scientific papers on the topic are the International Journal of Bank Marketing (two) and the International journal of Finance and Economics (two) The Web of Science claims that 20% of scientific papers that

thoroughly examine AI in banks are published in the ten top journals mentioned above (Figure 5).

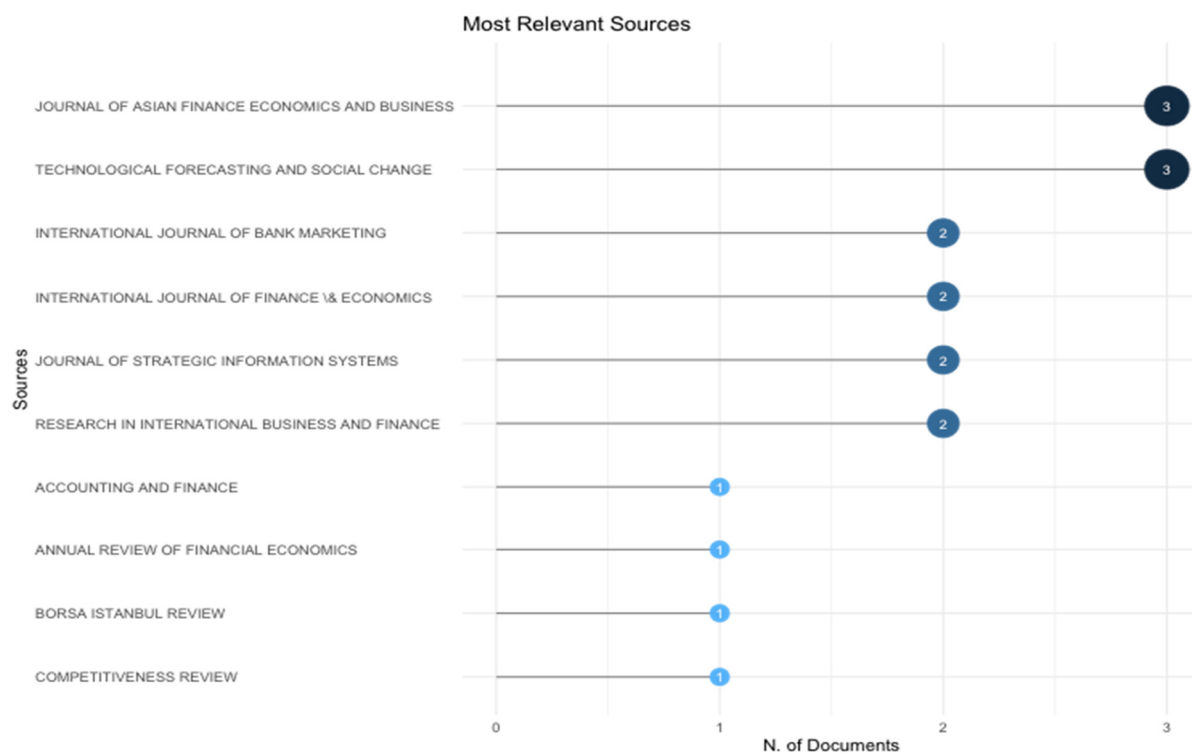


Figure 4. Top 10 most relevant sources. Note: The color intensity reflects the relative number of publications, with darker shades indicating higher values.

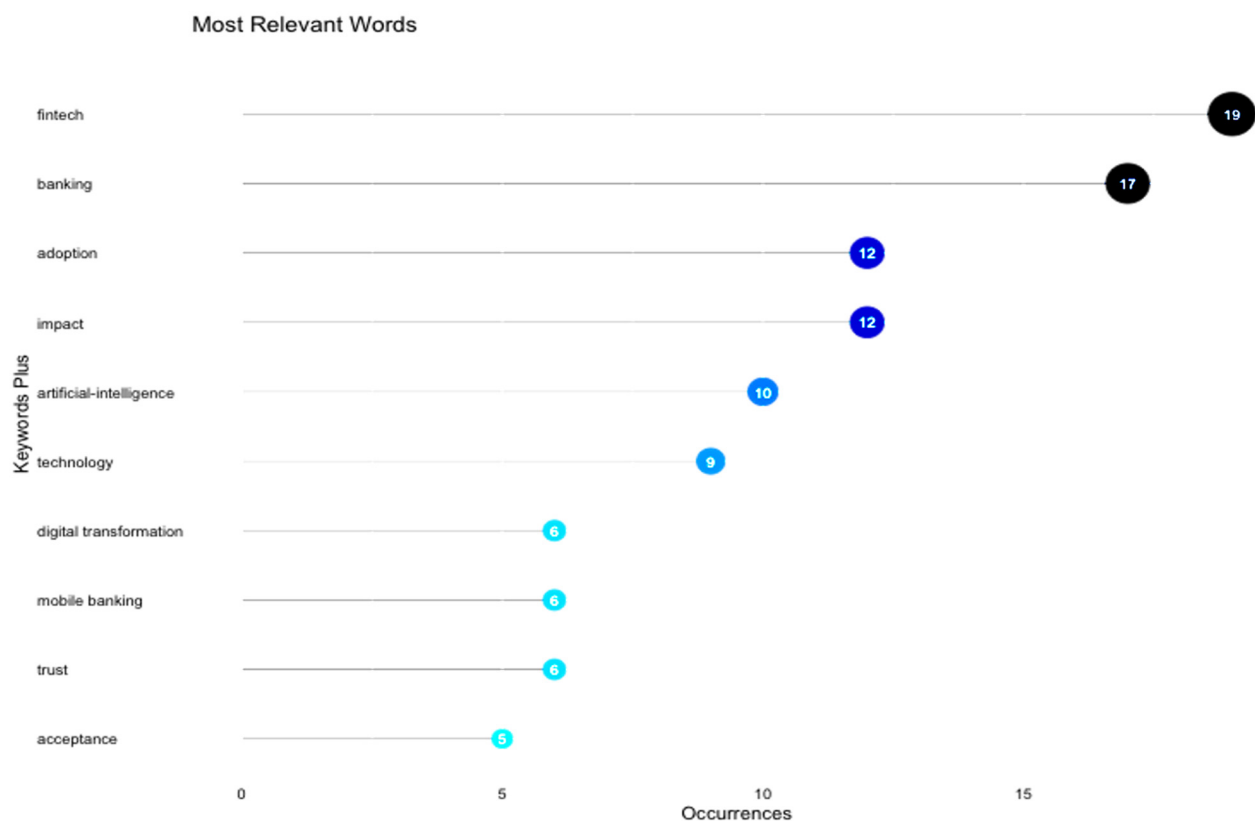


Figure 5. Most relevant words. Note: The color intensity reflects the relative number of publications, with darker shades indicating higher values.

Keyword co-occurrence analysis identifies clear thematic patterns in the literature. The presence of over 220 author keywords and 191 Keywords Plus terms indicates a varied vocabulary encompassing both technical and domain-specific elements. The clustering analysis identifies five major thematic clusters, reflecting the underlying conceptual structure observed across the abstracts and full texts:

- Credit Risk Modeling and Alternative Data Analytics, emphasis on machine learning, credit scoring, and data-driven borrower assessment (Chawla & Joshi, 2021; Ahmed et al., 2023; Mhlanga, 2021; Sawafta, 2021; Buzaubayeva et al., 2024).
- Fraud Detection and Anomaly Recognition, frequent keywords include “fraud detection,” “anomaly detection,” and “transaction monitoring,” reflecting continued scholarly interest in security and consumer protection (Ngai et al., 2011; Hassan et al., 2023; Davenport & Ronanki, 2018).
- AML and Financial Crime Analytics, studies applying AI to anti-money laundering (AML), suspicious activity detection, and regulatory reporting processes texts (Javaid et al., 2022; Zhang et al., 2020; Truby et al., 2022).
- Cybersecurity and Operational Risk, Topics include cyber-risk modeling, intrusion detection, operational disruptions, and system vulnerabilities, increasingly relevant given digitalization (Nourallah, 2023; Sang, 2024; Aria & Cuccurullo, 2017).

These clusters collectively illustrate a maturing thematic structure where technical, organizational, and regulatory concerns converge. Notably, governance-related keywords appear more frequently in recent publications, suggesting an emerging emphasis on responsible AI deployment in banking.

Figure 6 presents the network graph of keywords, illustrating the co-occurrence structure and relationships among the most frequently used terms in the analyzed literature. The visualization highlights major thematic clusters and reveals strong linkages between concepts related to artificial intelligence, banking, and risk management, indicating the intellectual structure of the research field. As shown in Figure 5, the density and proximity of keywords reflect the central research themes and their interconnectedness.

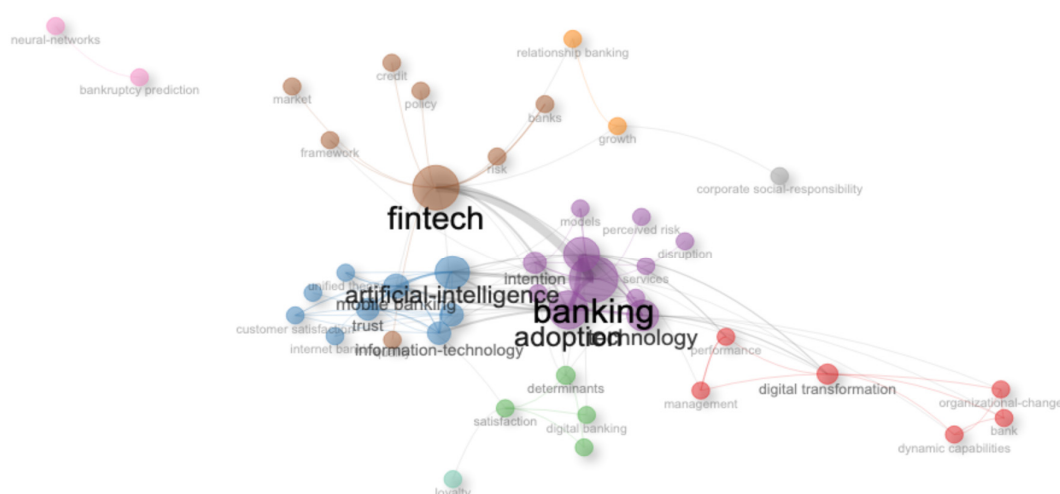


Figure 6. Network graph of keywords. Note: The color coding indicates clusters of related keywords identified using co-occurrence network analysis. Each color represents a distinct thematic group within the research field.

Figure 7 shows the essence of this clustering algorithm is to group concepts related to the topic under study, that is, to place them in four parts. As a result, they are grouped into Basic Themes, Niche Themes, Declining Themes, or Emerging and Motor Themes. As we can see from the figure, the placement of the concepts of “banking adoption impact,”

“digital transformation,” “satisfaction determinants,” and “digital banking, credit policy, and relationship banking” in the upper right corner indicates that these topics are well studied and are important for this field of study. These research topics are considered “motor” topics that characterize the central role and high density of specialization. Additionally, in the period under consideration in the study, the basic themes of the thematic map for all sectors (Basic Themes), “fintech framework market,” “banks growth,” and “corporate social responsibility” are located in the leading theme cluster, that is, these topics are considered research directions that are closely associated with other subjects in the investigation of the artificial intelligence problem in banks. Niche themes (Niche Themes), characterized by relatively weak connections with other areas of study, include “bank digital currency,” “endogenous money,” “structuralism,” and “consumer acceptance investment.” Research on “bankruptcy prediction” and neural networks is located in the cluster of emerging or declining themes (Emerging or Declining Themes). Meanwhile, research in the “fintech framework market” comprises essential and leading main topics.

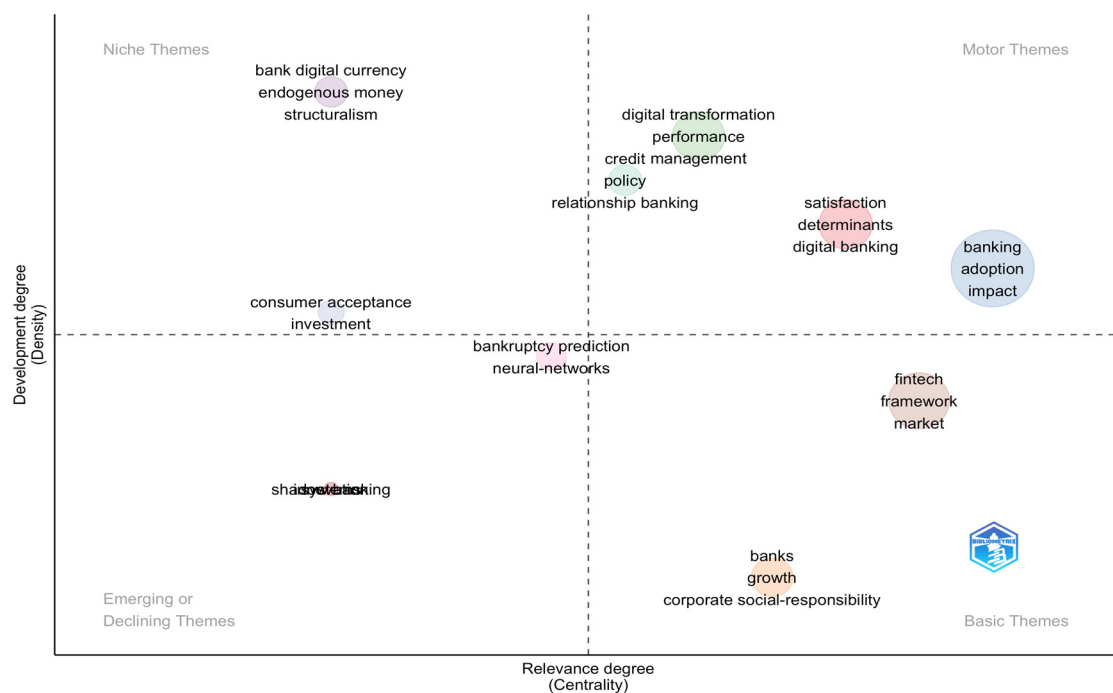


Figure 7. Thematic map of research. Note: The position of themes is based on centrality (x-axis) and density (y-axis), while colors represent different thematic clusters identified in the analysis.

As Figure 8 presents, the words ‘fintech,’ ‘banking,’ and ‘adoption’ are most frequent during the production period from 2020 to 2024. The word cloud of the most frequent terms provides a quick visual summary: terms like “fintech,” “banking,” “adoption,” “risk,” “machine learning,” and “fraud” are among the largest words, confirming their prominence in the literature. Notably, “fintech” and “banking” dominate, illustrating how closely tied fintech innovations (including AI) are to modern banking discourse. This reflects that many studies frame AI within the broader context of fintech development.

The conceptual structure derived from co-occurrence and thematic mapping indicates that research has evolved from algorithm-centric themes (e.g., machine learning model accuracy) toward integrated frameworks that include governance, ethical considerations, and institutional implementation. Motor themes, those that are both well-developed and central, include AI-supported credit risk assessment and fraud detection. Basic themes include compliance and operational risk, which are foundational but less technically specialized. Emerging themes relate to AI governance, explainability, and cyber-resilience.

laws (e.g., the EU 6th AML Directive) and advances in deep learning. The “operational risk” nature of this cluster is evident in that it deals with internal security and compliance. A concrete example is the surge of publications after 2017 on AI for fraud detection: this follows high-profile data breaches and a regulatory push for anomaly detection. Pattnaik et al. similarly identified an AML cluster, underscoring the global focus on financial crime prevention.

By contrast, the credit risk cluster has grown more steadily, reflecting ongoing interest in credit scoring models. Market risk research (Cluster 2) shows peaks around 2008 and 2020, corresponding to the global financial crisis and the COVID-19 market crash, when interest in forecasting spiked. Thus, major financial events and regulatory developments (e.g., Basel stress testing guidelines) appear to drive research emphases. Our analysis captures these trends in banking risk research and ties them to concrete causes.

The identified thematic structures and publication patterns are consistent with prior bibliometric studies in finance. For instance, Kuanova et al. (2025), using bibliometric analysis, reveal similar patterns of thematic clustering, research concentration, and the identification of leading contributors, confirming the robustness of bibliometric approaches in mapping financial research domains.

Our identified clusters largely echo those from earlier studies, but with new emphases. For instance, Pattnaik et al. and others noted fintech and risk mgmt themes; we confirm these and link them more precisely to bank risk types. The presence of a strong AML/fraud cluster in our results aligns with their “Anti-money laundering” cluster, validating that AI is intensively applied to financial crime detection. However, we also observed a notable cluster on “market risk and forecasting” that was not explicitly delineated in Pattnaik’s map (likely subsumed under general fintech in their analysis). This may be because prior work treated market risk as part of conventional finance, whereas we focused on risk domains explicitly.

In the realm of AI techniques, the “deep learning” theme is prominent in our operational risk cluster. This reflects AI maturity: deep neural networks are now being applied to unstructured data in banking. No prior bibliometric study we reviewed singled out deep learning in banking risk; thus, our results highlight this emerging shift. We also see relatively few papers on AI ethics or explainability (only a niche cluster on “AI fairness”); this gap suggests an opportunity for future work, as regulators increasingly stress responsible AI.

Overall, our cluster analysis confirms that AI-in-risk research is multidisciplinary (involving computer science, finance, and regulatory fields). It also uncovers new linkages: for example, we found a cross-theme involving “Big Data and Machine Learning” that bridges credit and operational risk, suggesting that banks are using large-scale datasets to manage various risks in tandem. These insights extend prior bibliometric findings by delving into the content of each cluster and its relevance to banking risk.

5. Discussion and Limitations

The results of the bibliometric analysis provide several important insights into the development of research on artificial intelligence in banking risk management. Overall, the findings reveal a rapidly expanding but still structurally fragmented research field characterized by strong interdisciplinary interactions among finance, computer science, and information systems.

First, the thematic analysis confirms that research on AI in banking risk management is strongly concentrated on credit risk modeling and fraud detection, which supports Analytical Expectation 1. These research areas dominate the keyword clusters and citation networks identified in the bibliometric analysis. This concentration reflects the practical im-

portance of AI technologies for reducing information asymmetry and improving predictive accuracy in financial decision-making. Previous studies have shown that machine learning algorithms outperform traditional statistical models in credit scoring and default prediction (Berg et al., 2020; Khandani et al., 2010). Similarly, AI-based anomaly detection systems have significantly improved banks' ability to detect fraudulent transactions and suspicious financial activities (Ngai et al., 2011). The prominence of these themes in the bibliometric network therefore confirms that AI technologies are most extensively applied in banking functions where large-scale data analysis provides substantial operational benefits.

Second, the findings provide evidence supporting Analytical Expectation 2 regarding the methodological evolution of research in this field. The keyword co-occurrence analysis indicates a growing presence of terms such as "machine learning," "deep learning," "big data," and "neural networks," suggesting a shift from traditional statistical methods toward more advanced computational approaches. This trend is consistent with broader developments in financial technology research, where AI-based models are increasingly used to analyze complex financial datasets and identify hidden patterns (Heaton et al., 2017). The increasing methodological sophistication of the literature also reflects the growing availability of financial data and advances in computational infrastructure that enable large-scale machine learning applications.

Third, the bibliometric analysis partially supports Analytical Expectation 3 regarding the structural concentration of research output. Although contributions originate from a wide range of countries, the results indicate that research activity is relatively concentrated among a limited number of regions and academic institutions. Countries such as China, the United States, the United Kingdom, and India appear particularly prominent in the dataset, reflecting their strong research capacity in both finance and artificial intelligence. Similarly, a relatively small group of journals accounts for a substantial share of publications, suggesting that the intellectual development of this field is shaped by a core set of academic outlets specializing in banking, financial technology, and digital innovation.

Beyond the confirmation of the proposed analytical expectations, the results also highlight several broader implications for research on AI-driven banking risk management. One important observation is the interdisciplinary nature of the field. The co-citation network demonstrates that influential studies originate from diverse research areas, including financial economics, machine learning, information systems, and regulatory policy. This interdisciplinary structure suggests that future research will likely continue to integrate insights from multiple disciplines in order to address the complex challenges associated with AI adoption in financial institutions.

Another important finding concerns the growing prominence of governance and regulatory issues related to AI deployment in banking. The keyword network reveals emerging themes related to explainable AI, algorithmic transparency, and regulatory technology. These topics reflect increasing concerns among policymakers and financial regulators regarding the potential risks associated with opaque machine learning models. As AI technologies become more deeply embedded in financial decision-making processes, issues such as model interpretability, fairness, and accountability are likely to become central research priorities.

Finally, the results suggest that the field of AI-driven banking risk management is transitioning from an early exploratory stage toward a more mature research domain. Early studies primarily focused on demonstrating the technical feasibility of AI applications in financial risk modeling. More recent research increasingly addresses broader organizational, regulatory, and strategic implications of AI adoption in banking institutions. This evolution indicates that future research will likely move beyond isolated algorithmic applications

toward more comprehensive analyses of how AI reshapes financial risk management systems and regulatory frameworks.

Taken together, these findings provide a clearer understanding of the intellectual structure and thematic evolution of research on artificial intelligence in banking risk management. The results highlight both the rapid expansion of the field and the need for greater theoretical integration and interdisciplinary collaboration to support the responsible adoption of AI technologies in financial institutions.

The bibliometric analysis reveals that research on artificial intelligence in banking risk management has developed rapidly since 2020 and is moving toward greater methodological maturity. The results highlight an expanding scholarly focus on applications such as fraud detection, credit risk modeling, anti-money laundering analytics, and cybersecurity, areas where AI demonstrates clear performance advantages over traditional risk management tools. The co-citation and keyword analyses confirm that these domains form the intellectual core of the field, reflecting both the priorities of financial institutions and the increasing regulatory emphasis on technology-supported supervision.

According to literature, studies consistently highlight the ability of AI-based models to improve predictive accuracy, reduce processing time, and enhance anomaly detection. These advantages are evident in research evaluating machine-learning-based fraud detection systems and in work assessing credit scoring and default prediction models. The thematic clusters emerging from the bibliometric mapping reinforce this pattern: the strongest clusters emphasize technical modeling approaches, financial crime analytics, and AI-enabled surveillance mechanisms. These findings indicate that AI is becoming deeply integrated into risk-sensitive processes and is no longer limited to experimental or conceptual applications.

In interpreting our results, it is useful to compare our thematic clusters with prior bibliometric studies. Comparison of thematic clusters: Gangwar et al. (2025) report clusters like fintech innovation, risk management, anti-money laundering, and actuarial science. These suggest that AI research in BFSI spans technical (fintech) and governance (AML) issues. Brika's FinTech study found clusters around blockchain, digital lending, and financial inclusion. In our findings, we observe related themes: for example, our "credit scoring" cluster is analogous to risk management, while our "cybersecurity/fraud" cluster overlaps with the AML-focused cluster of Gangwar et al. (2025). However, we also identify clusters less emphasized before (e.g., RegTech compliance). Thus, while our study confirms the presence of broad themes from previous work, our focus on banking risk yields a unique emphasis on, say, operational risk via AI and market risk modeling. We discuss these alignments and divergences below.

At the same time, the results show that the increased adoption of AI introduces new forms of risk and complexity. Model interpretability, algorithmic fairness, governance structures, and data quality remain recurrent concerns across highly cited studies. The presence of a distinct cluster focused on ethical and regulatory issues underscores that these challenges are viewed as central rather than peripheral to the future of AI-driven risk management. Research addressing these constraints stresses the need for transparent model architecture, robust oversight mechanisms, and regulatory frameworks capable of managing high-risk AI applications. The analysis confirms that these themes have grown more prominent in recent years, mirroring policy debates in major financial jurisdictions.

Another important insight is the fragmented nature of the scholarly landscape. The bibliometric network reveals dispersed collaboration patterns and the absence of a dominant theoretical or methodological paradigm. Contributions come from diverse disciplines, including computer science, finance, information systems, and management, which strengthens the field's interdisciplinarity but also contributes to conceptual fragmentation.

The structural mapping shows that the field remains in an early developmental stage, with limited integration between research streams focused on technical modeling, organizational readiness, regulatory design, and strategic implementation. This fragmentation is consistent with the small size of the core literature and the novelty of AI applications in high-stakes financial environments.

The evolution analysis indicates, however, that the field is undergoing consolidation. Research published after 2022 increasingly links technical innovations to governance considerations, customer-risk analytics, and institutional transformation. Emerging topics identified in the strategic diagrams, including AI for financial inclusion, explainable AI, and integrated risk-governance frameworks, suggest that researchers are moving from isolated application-specific studies toward broader examinations of how AI reshapes risk management at the organizational level. This thematic expansion signals that future work is likely to address systemic implications of AI, such as supervisory technology, cyber-resilience architectures, and enterprise-wide risk processes.

The results also demonstrate that the most influential publications in the dataset include foundational studies on digital transformation as well as focused empirical work on AI-enabled banking risks. Their prominence reflects the field's reliance on knowledge generated in adjacent domains such as FinTech, digital finance, and automation. This pattern suggests that the intellectual roots of AI-based risk management are broader than the emerging field itself and that conceptual and methodological contributions from other research areas continue to shape its development (Qahtani & Alsmairat, 2023).

Taken together, the analysis reveals a field characterized by rapid growth, expanding thematic depth, and increasing complexity. AI is now widely recognized as a transformative component of modern banking risk management, yet its integration requires parallel advancements in governance, regulatory design, and institutional capability. The findings highlight both the promise and the limitations of current research: while AI significantly enhances risk identification and prediction, its widespread adoption depends on addressing transparency, fairness, and oversight challenges.

Initially, our research is exclusively founded on English-language papers from the Web of Science. This creates a linguistic bias, as indicated in bibliometric literature; pertinent research in other languages may be overlooked. Future projects might involve non-English sources or the use of regional databases. Secondly, like to all citation-based analyses, our study is affected by citation lag bias: recent publications (2023–2024) may not have accrued numerous citations, resulting in an underestimation of their effect measurements. Subsequent revisions must to integrate altmetrics or extend the time frame. Third, we removed industry white papers and technical reports, which are significant in banking practice. This may exclude insights from rising practitioners. Subsequent research may integrate scholarly and industrial resources. Ultimately, our exclusive reliance on WoS may omit certain conference proceedings (e.g., IEEE/ACM) that feature early AI research. This approach was justified by the emphasis on journal literature; however, cross-database analysis may be conducted subsequently.

Despite these limitations, our revised research provides a thorough and contemporary perspective on AI in banking risk management, based on the existing literature.

In summary, the bibliometric results show that research on AI in banking risk management is transitioning from early experimental phases toward more integrated and multidisciplinary inquiry. The field is expanding in scope, yet remains fragmented, indicating substantial opportunities for theoretical consolidation and methodological convergence. These insights establish a foundation for outlining research priorities that can support the responsible advancement of AI in financial risk management frameworks.

Despite its broad contributions, the study acknowledges several limitations. The reliance on the Web of Science may exclude certain technical research streams concentrated in computer science databases such as IEEE, ACM, or Scopus. Citation-based metrics may undervalue recent high-quality papers with limited citation exposure. Furthermore, the analysis does not fully capture industry-led innovations documented in technical reports, patents, or proprietary datasets. Future research could integrate multiple bibliographic databases, conduct comparative analysis across regions, and explore the intersection of AI with emerging domains such as sustainable finance, quantum computing, and decentralized financial systems.

6. Conclusions

The purpose of this study was to provide a systematic bibliometric assessment of global research on the application of artificial intelligence in banking risk management over the period 2020–2024. By consolidating 83 publications identified through a rigorous screening process and analyzing them with established scientometric tools, the study mapped the structure, thematic evolution, and intellectual foundations of this emerging field.

The results show that academic interest in AI-driven risk management has expanded rapidly, with research increasingly addressing credit risk modeling, fraud detection, financial crime analytics, cybersecurity, and governance-related issues. The thematic clusters identified in the analysis indicate a shift from isolated algorithmic applications toward broader organizational, regulatory, and ethical considerations. At the same time, the intellectual structure of the field reveals significant fragmentation, reflecting contributions from diverse disciplines and the absence of a dominant theoretical or methodological framework.

From these findings, several conclusions can be drawn. First, AI has become a central component of contemporary risk management research, supported by evidence of improved predictive capability, enhanced surveillance functions, and more efficient decision processes. Second, the growing emphasis on transparency, fairness, and model governance highlights that the benefits of AI must be balanced against emerging forms of technological and operational risk. Third, the dispersed structure of the literature suggests that the field is still in a formative stage, underscoring the need for greater conceptual integration and cross-disciplinary collaboration.

These insights point to several avenues for future research. There is a need for studies that develop unified frameworks linking AI techniques to enterprise-wide risk management processes and supervisory expectations. More empirical work is required to evaluate AI performance in real-world banking environments, particularly in relation to model risk, explainability, and regulatory compliance. Additionally, greater attention should be directed toward understanding the organizational conditions that enable effective and responsible adoption of AI within financial institutions. Exploring these topics will support the development of a more mature and coherent body of knowledge and reinforce the practical relevance of AI-driven approaches to banking risk management.

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