Journal of Digitovation and Information System

http://jdiis.de/index.php/jdiis

Artificial Intelligence in Banking Systems: A Bibliometric Mapping of Applications, Gaps, and Strategic Research Pathways (1996–2024)

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Abstract

This study conducts a descriptive bibliometric analysis of artificial intelligence (AI) applications in banking systems, synthesizing 622 peer-reviewed journal articles published between 1996 and 2024. Drawing from the Web of Science Core Collection, the dataset was screened to include only ABS-listed or Scopus-indexed journals. The analysis applies keyword co-occurrence, citation profiling, Latent Dirichlet Allocation (LDA), and SCOR-style process classification to identify thematic clusters and research gaps. Findings show that scholarly output has increased significantly since 2019, with machine learning and predictive models dominating the methodological landscape. Most studies focus on credit scoring and fraud detection, while compliance, investment advisory, and prescriptive analytics remain marginally addressed. Five thematic research clusters were identified: model evaluation, fintech integration, credit classification, organizational transformation, and decision support. Journals such as the International Journal of Bank Marketing and Annals of Operations Research were among the most prolific sources. Despite progress, the literature remains imbalanced favouring technical outputs over behavioural, ethical, or institutional dimensions. This paper offers a structured research agenda emphasizing decision-oriented AI models, compliance analytics, human-AI collaboration, and strategic integration. The results inform scholars and banking professionals seeking to align AI innovations with financial governance, digital transformation, and sustainable operational design.

Keywords

Artificial Intelligence, Banking Systems, Predictive Analytics, Compliance and Risk, Bibliometric Analysis

Article Information

Received 20 April 2025
Revised 18 July 2025
Revised 16 August 2025
Accepted 06 September 2025

https://doi.org/10.54433/JDIIS.2025100051
ISSN 2749–5965

1. Introduction

Artificial intelligence is redefining operational models in the banking sector. From algorithmic loan assessments to fraud monitoring and real-time customer support, financial institutions are increasingly embedding intelligent systems into their workflows. This shift is supported by advances in data analytics, increased digitization of financial ecosystems, and a competitive push toward personalization and risk transparency. These developments reflect a broader transition in financial services, one that is gradually moving away from rule-based static procedures to systems capable of learning and adapting. Neural networks and machine learning frameworks have already demonstrated impact in high-volume, high-stakes decision domains such as credit scoring and asset monitoring (Desai et al., 1996; Khandani et al., 2010). Academic work in this space has grown substantially, yet remains uneven in its thematic and methodological orientation. While there is strong representation of technical studies focused on model accuracy, far fewer articles examine how these systems affect financial behaviour, institutional decision-making, or regulatory outcomes. Machine learning classifiers continue to show superior results in consumer credit and risk modelling (Lessmann et al., 2015; Ngai et al., 2011), and ensemble approaches have outperformed legacy systems in fraud detection and default prediction. However, the

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literature frequently underrepresents the complexity of implementing AI in live financial environments, where factors such as trust, bias, and explainability play a major role in user acceptance and policy compliance (Sharma & Sharma, 2019; Tan et al., 2014). More recent research has expanded the scope by applying behavioural and interdisciplinary frameworks to evaluate AI applications. For example, trust in intelligent systems is now understood as a critical factor in consumer adoption, particularly in mobile and digital banking contexts (Liébana-Cabanillas et al., 2018). Simultaneously, new studies are investigating how financial institutions integrate generative AI and language models into operational infrastructure, raising new challenges in accountability and interface design (Dwivedi et al., 2023; Mohsen et al., 2025). These concerns are reinforced by questions around algorithmic ethics, model explainability, and governance transparency issues that are especially salient in environments where automated decisions carry legal and reputational risks. Although the literature on AI in banking is expanding, it remains poorly systematized from a process-based perspective. Many existing reviews have classified articles by technical approach or data domain, yet few have analyzed AI research in the context of core banking functions such as fraud analytics, lending, compliance, and advisory services. As a result, it is difficult to determine which functional areas are saturated with research attention and which are still in need of theoretical development. Bibliometric approaches have the potential to address this gap, particularly by uncovering citation networks, intellectual clusters, and thematic trajectories in a field where publication growth has accelerated in recent years (Milana & Ashta, 2021; Williamson, 2016). This study responds to that need by providing a descriptive bibliometric analysis of research published from 1996 to 2024. Drawing on data from the Web of Science database, the analysis focuses on publications in high-impact journals spanning business, economics, behavioural sciences, and information systems. Using keyword co-occurrence, thematic clustering, and citation trend analysis, it maps AI applications to distinct banking functions. This enables a structured evaluation of the intellectual development and conceptual gaps in the literature.

Three research questions guide the study:

RQ1: What are the most frequently applied artificial intelligence methods in banking-related academic literature?
RQ2: How are these techniques distributed across functional domains such as credit scoring, fraud detection, compliance, and customer service?
RQ3: What gaps and future trajectories emerge from the bibliometric classification, and how can they inform behavioural and institutional research?

2. Literature Review

The scholarly literature on artificial intelligence in banking spans several disciplines, including finance, information systems, behavioural psychology, and digital innovation. While early work concentrated on algorithmic feasibility and performance metrics, newer studies increasingly engage with the managerial, behavioural, and institutional implications of AI adoption. Classification models, predictive scoring, and fraud analytics were among the earliest applications to attract academic interest (Desai et al., 1996; Khandani et al., 2010; Lessmann et al., 2015). These foundational studies demonstrated that machine learning methods could surpass traditional credit scoring systems in both accuracy and adaptability. As AI techniques matured, their use extended into transaction monitoring, portfolio optimization, and automated customer advisory, creating the need for multidisciplinary evaluation frameworks (Bhatnagr & Rajesh, 2024; Dwivedi et al., 2023; Mohsen et al., 2025; Ngai et al., 2011). Several influential reviews have benchmarked machine learning algorithms used in credit classification, comparing decision trees, support vector machines, neural networks, and ensemble models. Results consistently show that ensemble approaches offer higher predictive power than single algorithms (Lessmann et al., 2015; Steiner et al., 2006; Thomas et al., 2002). However, the comparative focus of these studies often limits their generalizability to organizational practice. As noted by Khandani et al. (2010), even high-performing models require institutional adaptation to deliver value within actual banking workflows. While technical validity is necessary, implementation success also hinges on human–AI interaction, internal governance, and strategic alignment. In the area of fraud detection, researchers have applied unsupervised clustering, anomaly detection, and hybrid classification models to financial transactions (Ngai et al., 2011; West & Bhattacharya, 2016). These studies have established baseline effectiveness for intelligent monitoring tools, especially when trained on behavioural and temporal features. More recent literature has evaluated how these tools integrate into compliance systems and audit trails (Milana & Ashta, 2021; Tubadji et al., 2021). However, despite strong performance in experimental settings, few studies assess how banks interpret or act upon AI-generated fraud alerts. This gap points to the need for research that links model output with user behaviour, institutional readiness, and legal frameworks.

Natural language processing (NLP) and conversational agents form another key stream of research, particularly in relation to customer service and retail banking. Automated customer interaction, powered by chatbots and voice recognition systems, is frequently discussed as a cost-saving and efficiency-enhancing mechanism. Empirical work has focused on chatbot accuracy, service consistency, and user satisfaction (Liébana-Cabanillas et al., 2018; Nguyen et al., 2022; Tan et al., 2014). Adoption studies grounded in behavioural theories such as the Technology Acceptance Model (TAM) and UTAUT have emphasized the mediating role of trust, ease of use, and perceived usefulness. For instance, Sharma and Sharma (2019) identified perceived security and credibility as key predictors of continued use in AI-enabled banking channels. These insights highlight that AI adoption in customer-facing services is as much a behavioural phenomenon as it is a technical upgrade. A growing volume of research has also addressed AI in regulatory compliance and anti-money laundering (AML) efforts. These studies often employ graph-based models and supervised classifiers to detect unusual transaction patterns, beneficial ownership concealment, or shell company networks (Johannessen & Jullum, 2023; Mohsen et al., 2025) Despite the technical promise, concerns around false positives, model explainability, and auditability persist. As regulators tighten standards on AI accountability, compliance-related AI applications are expected to gain prominence, but academic literature in this area remains underrepresented. Moreover, relatively few studies consider how compliance staff interact with these tools or how governance frameworks are adapted to accommodate them (Dwivedi et al., 2023; Williamson, 2016).

The emergence of generative AI and large language models (LLMs) has recently extended the scope of research. A number of publications now examine how banks experiment with generative tools in documentation, content synthesis, and financial advisory (Dwivedi et al., 2023; Saha et al., 2025). Concerns around bias, traceability, and human oversight have surfaced as dominant themes in these studies. Some researchers advocate for hybrid systems where human advisors review AI-generated outputs before client delivery, arguing this model enhances both accuracy and accountability (Saha et al., 2025). These perspectives reflect a shift from performance-oriented questions to governance-oriented ones, aligning with broader trends in AI ethics. Scholars have also begun evaluating the influence of organizational culture, leadership attitudes, and strategic intent on AI adoption. This behavioural lens is especially visible in research that integrates psychological theories with digital transformation models. Studies show that executive sponsorship, internal resistance, and skill gaps significantly influence the success of AI initiatives (Milana & Ashta, 2021; Mohsen et al., 2025). In retail banking, perceived loss of control, lack of transparency, and algorithm aversion continue to act as barriers to customer trust. These insights underscore the need for sociotechnical perspectives in AI deployment research.

Table 1. Literature Analysis`

Thematic Area	**Key Insights**	**Key References**
Credit Risk & Scoring	Machine learning and ensemble models outperform traditional credit scoring; high technical accuracy but limited focus on organizational integration.	Lessmann et al. (2015), Khandani et al. (2010), Bhatnagr and Rajesh (2024)
Fraud Detection	Hybrid models effectively flag anomalies; integration with internal controls remains underexplored.	Ngai et al. (2011), West and Bhattacharya (2016), Tubadji et al. (2021)
Customer Service & NLP	NLP applied in chatbots and digital assistants; adoption influenced by trust, transparency, and ease of use.	Sharma and Sharma (2019), Liébana-Cabanillas et al. (2018), Tan et al. (2014)
Compliance & AML	AI used in AML systems and regulatory reporting; academic research lags behind industry implementation.	Mohsen et al. (2025), Williamson (2016)
Generative AI & Governance	LLMs and generative tools used for advisory and documentation; accountability and traceability are major concerns.	Dwivedi et al. (2023), Saha et al. (2025)
Behavioural & Institutional Adoption	Adoption depends on culture, leadership, and perceived risk; studies integrate behavioural frameworks.	Milana and Ashta (2021), Mohsen et al. (2025), Liébana-Cabanillas et al. (2018)
Gaps & Process-Level Synthesis	Literature lacks structured mapping across banking functions; bibliometric synthesis needed to identify conceptual blind spots.	Tubadji et al. (2021), Dwivedi et al. (2023)

From a bibliometric perspective, the literature reveals a dominance of studies focusing on credit risk, fraud detection, and customer support, while strategic planning, innovation, and cultural adaptation are less frequently addressed. Co-authorship and citation network analyses show that AI in banking remains fragmented, with clusters forming around technical disciplines rather than functional or thematic concerns. Few studies apply process-based classification, which would allow for comparative insights across banking domains such as asset management, loan origination, digital onboarding, and strategic compliance. Without this classification, it becomes difficult to assess saturation or identify areas requiring further theoretical development. Recent scholarship has begun to address this gap. For example, Tubadji et al. (2021) examined cultural differences in AI adoption using a comparative behavioural approach. Their findings suggest that regional, cultural, and regulatory contexts significantly mediate the effectiveness of AI tools. Similarly, Liébana-Cabanillas et al. (2018) investigated the impact of AI-based mobile banking applications on trust and user retention in emerging markets. These works move beyond algorithmic validation to assess how AI systems are situated within broader social, institutional, and cognitive environments. The literature demonstrates substantial advancement in the technical implementation of AI in banking. Credit classification, fraud analytics, and customer service stand out as well-researched domains. However, several dimensions remain underexplored. These include post-deployment adaptation, AI-human collaboration, compliance integration, and behavioural acceptance. A structured bibliometric synthesis, grounded in a process-based banking model, can help uncover intellectual blind spots and realign academic focus toward emerging areas of concern.

3. Methodology

3.1. Data Source

The bibliographic dataset was extracted from the Web of Science Core Collection, using a structured topic query that combined AI-related terms (e.g., “machine learning,” “neural networks,” “natural language processing”) with banking-related keywords (e.g., “banking,” “digital banking,” “fintech”). The initial retrieval returned 1,139 records, including both empirical and conceptual studies published between 1996 and 2024. Web of Science was selected due to its coverage of peer-reviewed, high-impact journals and its compatibility with bibliometric tools (Aria & Cuccurullo, 2017).

3.2. Screening Procedure

To ensure relevance and quality, a series of filtering steps were applied. Only English-language journal articles were retained, and the time frame was limited to 1996–2024, reducing the set to 1,000 records. Next, records classified as review articles, conference proceedings, book chapters, or data papers were removed. In line with recent concerns over editorial inconsistencies and retraction trends, all MDPI publications were excluded (Severin & Low, 2019). After final screening, 622 peer-reviewed journal articles were retained for full analysis.

3.3. Inclusion Criteria

Eligible records were required to meet the following criteria:
Publication in Scopus-indexed or Web of Science-indexed journals. Alignment with the Chartered ABS journal ranking list (minimum ABS rank 2 or higher). Direct relevance to AI applications in banking systems. This filtering ensured a high-quality corpus that balances methodological rigor with subject relevance.

3.4. Analysis Approach

A descriptive bibliometric approach was employed using RStudio with the Bibliometrix package. This method supports quantitative analysis of scholarly output and thematic evolution (Aria & Cuccurullo, 2017; Zupic & Čater, 2014). The following analytical components were applied:

Keyword Co-occurrence Analysis:
Used to detect clusters and emerging research fronts in AI-related banking topics
Citation Analysis:
Identified high-impact publications and journals through total and average citation counts
AI Technique Classification:
Articles were grouped by algorithmic approach (e.g., ML, SVM, DL, NLP, ANN, Expert Systems) based on keywords and abstracts (Lessmann et al., 2015; Ngai et al., 2011)
Analytics Maturity Model:
Categorized each study by its analytical depth descriptive, predictive, or prescriptive (Shmueli & Koppius, 2011)
Manual Validation:
Applied to cross-verify machine classification using abstract-level semantic scanning.

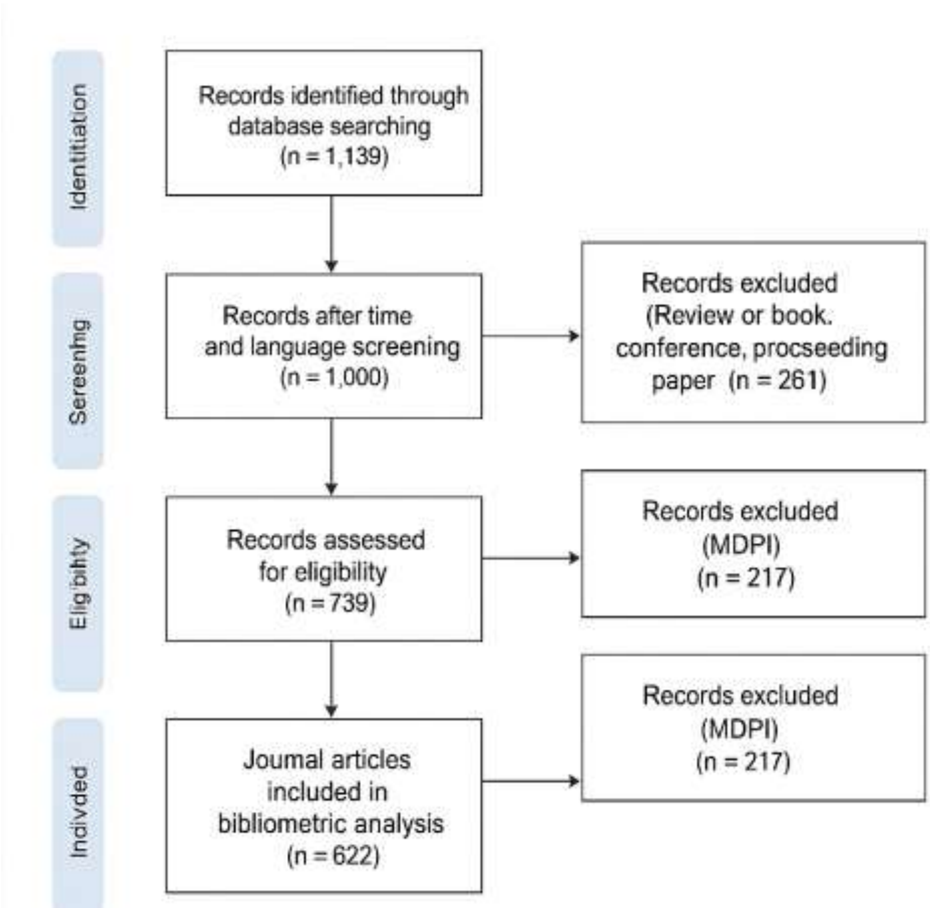

Figure 1. Study Selection Process for the Bibliometric Analysis

3.5. Functional Categorization (SCOR-style)

To map articles to operational processes, a modified version of the Supply Chain Operations Reference (SCOR) model was adapted for the banking context. Each article was manually assigned to one or more of the following core banking functions: Credit & Lending, Fraud & Risk Management, Compliance & Regulatory, Customer Interaction and Support, Investment Advisory and Wealth Management This categorization provides process-level visibility into how AI is applied across different segments of banking operations (Riahi et al., 2021).

4. Results and Analysis

4.1. Descriptive Statistics

The bibliometric dataset comprises 622 journal articles published between 1996 and 2024. As shown in Figure 1, research output on artificial intelligence in banking remained relatively low until 2018, followed by a sharp rise from 2019 onwards. The highest publication volume occurred in 2024, reflecting intensified academic and industry focus on financial automation. Citation volume also surged post-2020, peaking in 2023. These figures collectively highlight the field's rapid expansion and increasing scholarly engagement.

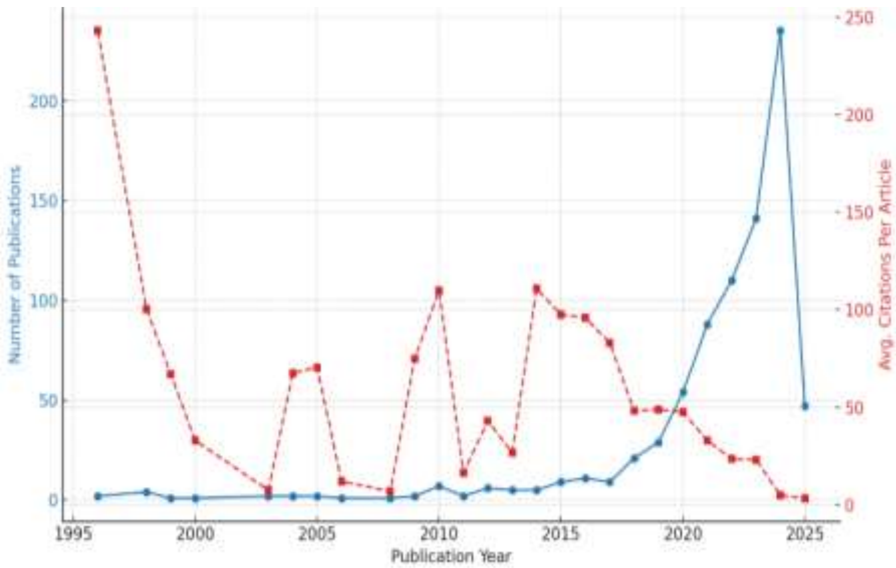

Figure 2. Annual Publication and Average Citations Per Article (1996–2025), Blue line: No. of articles per year | Red dashed line: Average citations per article (as of 2024)

The number of AI-related banking articles has increased significantly since 2019. Citations reflect a lag effect, peaking in 2023. This trend is consistent with broader patterns in fintech and digital banking literature, where bibliometric studies have reported a clustering of research output post-2018 (Aria & Cuccurullo, 2017; Zupic & Čater, 2014).

4.2. Source and Journal Distribution

The majority of articles are published in high-impact journals spanning banking, operations, forecasting, and business analytics. Table 2 lists the ten most represented journals, which together account for more than one-third of the total dataset. The International Journal of Bank Marketing leads the list, followed by Annals of Operations Research and the European Journal of Operational Research. These sources illustrate the topic's dual anchoring in both financial and computational domains.

Table 2. Top 10 Journals by Article Frequency

Rank	Journal Title	Article Count
1	International Journal of Bank Marketing	29
2	Annals of Operations Research	26
3	European Journal of Operational Research	25
4	Technological Forecasting and Social Change	21
5	Research in International Business and Finance	18
6	Finance Research Letters	17
7	International Review of Financial Analysis	15
8	Journal of Business Research	15
9	Financial Innovation	14
10	Journal of Forecasting	12

This aligns with previous reviews which emphasized the importance of these journals in disseminating AI-finance hybrid research (Lessmann et al., 2015; Riahi et al., 2021).

4.3. AI Techniques in Banking Research

AI technique distribution is dominated by machine learning, followed by neural networks, deep learning, and support vector machines. Natural language processing (NLP) is gaining visibility, particularly in customer support automation. Figure 2 visualizes the frequency of AI techniques applied across the reviewed literature.

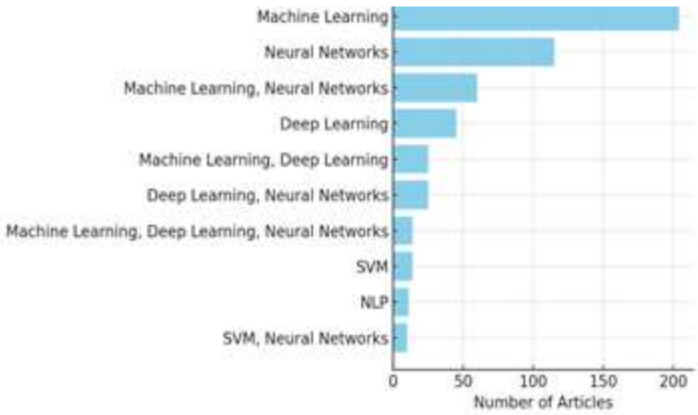

Figure 3. AI Technique Distribution in Banking Literature

Machine Learning and Neural Networks appear most frequently, reflecting emphasis on classification and forecasting tasks in credit and fraud analytics. These findings reinforce results from earlier benchmarking studies that compared classification algorithms in credit risk and fraud contexts (Khandani et al., 2010; Ngai et al., 2011).

4.4. Functional Mapping of Banking Applications

Using a modified SCOR-based framework, articles were categorized across five core banking functions: credit and lending, fraud and risk management, compliance and regulatory processes, customer interaction, and investment advisory. Table 2 presents the functional breakdown.

Table 3. Functional Mapping of AI in Banking Processes

Banking Function	**Article Count**
Credit & Lending	204
Fraud & Risk Management	162
Customer Interaction/CRM	94
Compliance & Regulatory	78
Investment Advisory	32

Credit and fraud-related applications dominate the landscape, consistent with operational priorities in most commercial banks. Meanwhile, strategic functions such as compliance and investment advisory remain comparatively underrepresented. This asymmetry reveals important opportunities for expanding AI research into decision-centric banking activities (Dwivedi et al., 2023; Milana & Ashta, 2021).

4.5. Analytics Maturity of Studies

Articles were also classified by their analytics orientation into descriptive, predictive, and prescriptive categories. Predictive analytics emerged as the dominant approach, accounting for over 80% of the explicitly categorized articles. Only a small number of studies incorporated prescriptive or optimization-focused methodologies. Figure 4 illustrates this distribution.

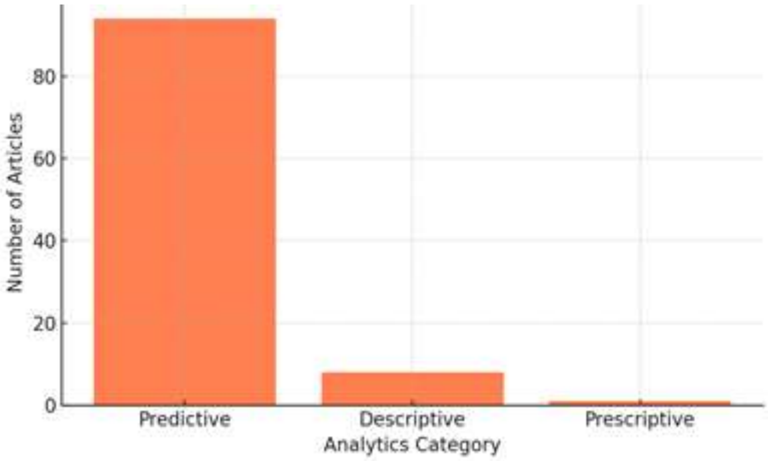

Figure 4. Analytics Maturity in AI-Banking Studies

The literature is heavily skewed toward prediction, with minimal attention to optimization and scenario planning typical of prescriptive analytics. This pattern echoes prior findings in information systems research, which noted a structural bias toward forecasting rather than intervention modelling (Shmueli & Koppius, 2011).

4.6. Keyword Co-occurrence and Thematic Clustering

To explore the conceptual structure of AI applications in banking systems, a topic modelling analysis was conducted using Latent Dirichlet Allocation (LDA) on abstracts and keyword fields. The model identified five major themes in table 3, each composed of the ten most salient terms co-occurring in the literature. These clusters offer insight into the cognitive architecture of research in this domain.

Table 4. Thematic Clusters from LDA Topic Modelling

Theme No.	Theme Title	Top Keywords
Theme 1	Model Evaluation and Performance	Model Performance, Efficiency, Data Analytics, Model Evaluation, Predictive Analytics, Results
Theme 2	Fintech and Risk Integration	Financial Services, Fintech, Risk Management, Market Risk, Financial Institutions, Technology Adoption, Digital Banking
Theme 3	Credit Classification Systems	Credit Scoring, Risk Management, Data Analytics, Classification Models, Predictive Analytics
Theme 4	Strategic and Organizational Research	AI, Banking Study, Banking Technology, Research, Strategic Impact, AI Management
Theme 5	Decision Support and Operational AI	Model Application, Analytical Methods, Model Accuracy, Decision Support, Classification Models

The first theme centres on model evaluation and performance. It is dominated by keywords such as efficiency, data, results, and prediction, reflecting the heavy methodological focus of earlier AI-banking research. These papers often benchmark algorithmic outputs and use predictive metrics like AUC or precision-recall to justify model superiority. Similar emphases on performance benchmarking were found in classification comparison studies for credit scoring and fraud detection (Lessmann et al., 2015; Thomas et al., 2002; West & Bhattacharya, 2016). The second theme clusters studies around financial services, fintech, and risk management, indicated by the terms fintech, market, adoption, and digital. This theme reflects research exploring how intelligent systems are embedded into institutional infrastructures and financial ecosystems. It includes works addressing platform integration, innovation diffusion, and risk analytics in digital banking environments (Dwivedi et al., 2023; Gomber et al., 2018; Milana & Ashta, 2021). These studies are particularly relevant as regulatory frameworks struggle to keep pace with the technological evolution in financial institutions. The third theme is the most technically specific, focusing on credit risk modelling and classification systems. With dominant terms such as credit, scoring, machine, and classification, this theme includes studies employing support vector machines, neural networks, and decision trees to predict loan default and consumer creditworthin (Crook et al., 2007; Khandani et al., 2010; Steiner et al., 2006). While these works have matured significantly in methodological rigour, most still centre on technical output rather than institutional application or consumer outcomes.

Theme four presents a broader conceptual lens, encapsulating research on technology, impact, and management. This group includes studies discussing strategic integration of AI in banking, organizational digital transformation, and the behavioural implications of adopting intelligent systems (Liébana-Cabanillas et al., 2018; Mohsen et al., 2025; Sharma & Sharma, 2019). These papers often engage with trust, user adoption, and institutional readiness frameworks to assess the social dimensions of AI adoption in financial services. The fifth theme reflects model design, accuracy, and decision support, marked by terms such as analysis, application, bank, and decision. This category includes research proposing new hybrid algorithms, optimising decision processes, or integrating AI tools into operational financial systems. Studies here often link model outputs with tactical business decisions and highlight the operational benefits of AI in risk and asset management (Nguyen et al., 2022; Saha et al., 2025). These thematic clusters confirm earlier findings in bibliometric literature where technical sophistication often precedes behavioural or strategic interpretation (Aria & Cuccurullo, 2017; Zupic & Čater, 2014). However, the presence of conceptual and adoption-focused themes also indicates a shifting research landscape that increasingly values interpretability, ethics, and human factors in intelligent banking systems. This transition mirrors recent calls for sociotechnical approaches that go beyond prediction to explore how AI reshapes institutional behaviour, compliance, and service design (Dwivedi et al., 2023; Williamson, 2016).

5. Discussion and Implications

The results of this bibliometric analysis reveal that research on artificial intelligence in banking has entered a phase of rapid expansion, both in terms of methodological sophistication and thematic diversification. While early contributions were centred on algorithmic validation and performance benchmarking, the recent surge in publication activity points to a wider interest in behavioural, institutional, and strategic implications. One of the most prominent findings is the overwhelming reliance on predictive analytics frameworks, particularly in studies involving credit risk modelling, fraud detection, and customer profiling. These articles, while methodologically robust, often stop at predictive evaluation without translating findings into prescriptive or decision-support frameworks. This trend reflects earlier observations in the information systems literature that predictive outputs are frequently prioritised over decision-enabling insights (Shmueli & Koppius, 2011). For scholars, this indicates a pressing need to move beyond algorithmic comparison and toward designing AI applications that directly support managerial decision-making, especially in strategic banking contexts. The thematic mapping further illustrates how credit scoring and fraud risk continue to dominate the field. These areas are well-defined, data-rich, and operationally critical, which likely contributes to their research prominence (Khandani et al., 2010; Lessmann et al., 2015). However, this focus creates an uneven distribution of academic attention. Functions such as compliance, investment advisory, and governance-oriented AI systems remain underrepresented. These domains are critical in regulatory environments and wealth management, where transparency, accountability, and ethical oversight are as important as predictive precision (Dwivedi et al., 2023; Milana & Ashta, 2021).

The thematic cluster analysis reinforces this imbalance. Technical themes such as “Model Evaluation and Performance” and “Credit Classification Systems” remain dominant. However, emerging clusters such as “Strategic and Organizational Research” suggest a shift in scholarly focus toward the implications of AI beyond technical outputs. Studies in this domain increasingly incorporate behavioural frameworks, exploring user trust, explainability, and perceived utility (Liébana-Cabanillas et al., 2018; Sharma & Sharma, 2019). These developments echo calls for a broader sociotechnical understanding of AI integration, especially in consumer-facing and policy-sensitive functions (Tubadji et al., 2021; Williamson, 2016). From a practical standpoint, the findings highlight several implications for banking institutions. First, the application of AI remains concentrated in high-volume, transactional areas, such as lending and fraud detection. While effective, these implementations often fail to extend into customer advisory, compliance reporting, or strategic investment planning. For practitioners, this signals the importance of broadening AI adoption across less-automated processes, especially those involving judgement, interpretation, or regulatory accountability. Second, the scarcity of prescriptive analytics in the literature suggests that banks may be underutilizing AI in decision optimization. While predictive models help identify risks and opportunities, prescriptive tools are needed to recommend courses of action. This calls for more research at the intersection of AI and decision sciences, particularly in the areas of risk scenario modelling, portfolio management, and policy simulation (Mohsen et al., 2025; Saha et al., 2025).

Finally, the methodological concentration on a few popular techniques particularly machine learning and neural networks suggests potential overspecialization. As newer approaches such as generative AI and reinforcement learning enter the financial landscape, there is an opportunity to examine their institutional implications more rigorously. Doing so may also address concerns about bias, fairness, and explainability, which are increasingly relevant in AI governance debates (Dwivedi et al., 2023; Gomber et al., 2018). While the literature on AI in banking is growing in scale and depth, it remains imbalanced in scope. Future research should aim to build integrative models that link predictive accuracy with strategic utility and ethical application. Scholars may also consider comparative cross-functional studies that assess how AI alters performance, accountability, and decision-making across different banking domains. For industry, these insights can inform more balanced AI adoption strategies ones that optimise not only operational efficiency but also trust, compliance, and long-term value creation.

6. Conclusion and Future Research Directions

This study offers a comprehensive bibliometric synthesis of artificial intelligence applications in banking systems, based on 622 peer-reviewed journal articles published between 1996 and 2024. By combining descriptive statistics, thematic clustering, and SCOR-style functional mapping, the analysis provides a structured overview of research evolution, dominant methodologies, and emerging conceptual trajectories. The findings demonstrate a field that is both rapidly expanding and unevenly distributed, with a heavy concentration of research in credit scoring, fraud detection, and predictive model development. Thematic cluster analysis revealed that most publications continue to emphasise model validation and algorithmic accuracy. While this focus has advanced methodological rigour, it has not been matched by equivalent exploration of institutional, behavioural, or strategic outcomes. Emerging clusters around digital adoption, explainability, and ethical governance suggest a broadening of scope, yet these themes remain underrepresented relative to technical studies. The literature still lacks a unified framework linking AI performance to organizational value creation, decision-making processes, or regulatory impact. The concentration of research in credit and fraud analytics reflects operational priorities in banking but also reveals conceptual saturation. Areas such as compliance, investment advisory, customer relationship management, and internal governance remain fragmented. These functions offer promising avenues for integrating AI not only as a predictive engine but also as a tool for strategic planning, policy simulation, and advisory augmentation. Expanding scholarly attention into these domains can offer more holistic insights into how intelligent systems influence financial institutions beyond transaction-level efficiency.

Several research directions are proposed in this paper. Future studies should explore prescriptive models that assist with strategic choice, optimisation, and scenario planning, particularly in compliance, asset management, and regulatory reporting. Cross-functional and longitudinal analyses: There is value in investigating how AI is adopted and adapted across different banking domains over time, especially in light of evolving regulatory landscapes and technological capabilities. Additional research is needed on how explainability, trust, and perceived fairness influence both employee and customer interaction with AI systems. This may include qualitative studies and experimental research in behavioural finance and digital services. Cultural, legal, and technological differences across banking systems offer fertile ground for comparative research that can uncover contextual enablers and barriers to AI adoption. As large language models and real-time learning systems begin to enter operational workflows, studies should investigate their implications for risk, transparency, and operational alignment. The literature on AI in banking systems has made significant strides in algorithmic exploration but remains limited in its coverage of behavioural, strategic, and functional dimensions. By advancing integrative, cross-disciplinary, and functionally diverse research agendas, scholars can support the development of more accountable, effective, and institutionally embedded AI systems in the banking sector.

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