

Mapping the Evolution of Artificial Intelligence in Banking: A Systematic Bibliometric Review of Research Trends, Techniques, Applications, and Emerging Challenges

Ayoub LOUHAB, (Doctoral student)

Modelling applied to economics and management MAEGE.
Faculty of Sciences Legal, Economic and Social Sciences Ain Sebaa
Hassan II University of Casablanca, Morocco

Abdelhak YAACOUBI, (Full Professor)

Modelling applied to economics and management MAEGE.
Faculty of Sciences Legal, Economic and Social Sciences Ain Sebaa
Hassan II University of Casablanca, Morocco

Mohamed AZOUAZI, (Full Professor)

Information Technology and Modelling Laboratory MITI
Faculty of Sciences Ben M'sick
Hassan II University of Casablanca, Morocco

Correspondence address :	FSJES AIN SEBAA Route des Chaux et Ciments Beausite «BP : 2634 «Casablanca 20254
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Abstract

Artificial intelligence (AI) development has revolutionized the financial industry, providing solutions for better fraud detection, credit risk assessment, customer relationship management, bank operations and regulation. Despite numerous publications dedicated to the topic in question, there are no bibliometric studies devoted to exploring the development, structure of knowledge bases and trends in research on AI applications in banking. Therefore, to fill the gap, this paper provides a systematic review of the existing literature concerning the application of AI in banking based on a dataset of 114 papers indexed in Scopus from 2020 to 2025. The systematic approach is applied to the research based on the methodology described in the PRISMA guidelines and such analytical tools as Bibliometrix, Biblioshiny and VOSviewer are used to assess the scientific output, key sources of information, Institutions and countries and thematic links via keyword co-occurrences. Thus, the annual increase rate of publication number in this area is estimated at 39.77% and involves 96 publication sources and 394 authors. Moreover, six topical issues related to the field under investigation are revealed, including fraud detection using machine learning techniques, credit and risk management, digital banking, cybersecurity, customer-focused applications and explainable AI. The overall findings from the findings indicate that the research is moving from the stage of developing individual algorithms to building a holistic approach towards developing intelligent banking systems that can be regulated. Through integrating bibliometric analysis with an extensive review on the use of AI in banking, this paper adds to the existing body of knowledge and identifies new areas for research in explainable AI, data governance, ethical implementation, and intelligent financial services.

Keywords: Artificial Intelligence; Banking; Machine Learning; Fraud Detection; Risk Management; Bibliometric Analysis; VOSviewer; Bibliometrix.

JEL Classification: G21, G28, O33

Paper type: Theoretical Research and Empirical Research

1. Introduction

Artificial Intelligence (AI) is becoming a fundamental pillar of innovation in the banking industry and dramatically changing the functioning and service offering of financial organizations (Abdulsalam & Tajudeen, 2024). The fast-growing popularity of digital banking, the constant increase in financial transactions, the amount of available data, and the rise of complex cases of financial crimes have brought both new prospects and challenges to banks (Sabidi & Zolkipli, 2024). Under these new conditions, financial organizations resort to using AI-enabled solutions for improving operational efficiency, decision-making, regulatory compliance, and service delivery (Elumilade et al., 2025). Thus, AI has transformed from a supportive technology into a strategic tool allowing banks to gain competitiveness against the backdrop of a dynamic financial environment (Oyegbade et al., 2023).

The constant development of such domains as machine learning, deep learning, natural language processing, computer vision, predictive analytics, and explainable artificial intelligence has greatly expanded the sphere of applications of AI in modern banking (Vuković et al., 2025). Today, the use of the technologies described is widespread as they are used for the purposes of detecting fraud, preventing money laundering (AML), assessing credit risks, optimizing portfolios, protecting against cyberattacks, managing customer relationships, and making decisions about finances intelligently (Amoako et al., 2025). Compared to conventional rule-based models, machine learning models can process large financial datasets, learn from both historical and current transactions, detect hidden behavioral patterns, and adapt to new schemes of fraud. Therefore, today the use of artificial intelligence in digital transformation processes has become critical (Oyekunle & Boohene, 2024). Along with the increasing importance of AI in the banking industry, there has been rapid growth in scientific literature focused on intelligent banking systems (Fares et al., 2022). The latest scientific works analyze various applications of AI in the following areas: fraud detection, financial forecasts, credit scoring, digital banking, robo-advisory, RegTech, customer experience, operational risk management (Ali et al., 2022). Concurrently, various systematic and bibliometric reviews have been performed to provide a synthesis of the rapidly increasing body of literature in the field of AI for financial services. Such efforts have been useful in revealing important technological trends, new research directions, and the development of AI research in various parts of the financial industry (Ahmadi, 2024). Notwithstanding the impressive increase in the amount of research on artificial intelligence in financial services, several systematic and bibliometric reviews have analyzed the increasing presence of AI technology in a few financial activities (Bello et al., 2023). The contribution of such research is noteworthy in terms of understanding publication practices, prominent researchers, research collaboration networks, and new research topics associated with finance, fintech, fraud detection, financial risk management, and digital transformation (Li & Xu, 2021). Unfortunately, the scope of such studies has been too broad to consider banking separately from other branches of the financial industry, which include insurance, capital markets, and fintech. Furthermore, most of the existing bibliometric studies have mostly centered on scientific production, citations and keyword co-occurrences without placing enough emphasis on the way in which the bibliometric findings may be utilized for AI applications in banking. In fact, there is a need to pay attention to the fast-growing developments around explainable AI, generative AI, responsible AI, and data governance among others. The fast changes within this sector have influenced research priorities and technological developments, hence, rendering the earlier reviews partly outdated. Such developments make it necessary for the current bibliometric investigation to consider the intellectual and conceptual evolution of AI research in the banking field and the integration of bibliometric evidence and synthesis of technological developments within the domain.

In this regard, the present paper provides a detailed bibliometric review aimed at investigating the scientific development of AI in the banking industry and identifying future research directions. To bridge this research gap, the current study will use a systematic bibliometric analysis of AI applications in banking through publications covered by the Scopus database from 2020 to 2025. This study will be carried out according to the PRISMA guidelines and will use Bibliometrix, Biblioshiny, and VOSviewer in studying the literature dynamics, scientific productivity, key journals, key authors, institutional and international collaboration, and the literature's conceptual structure through keyword co-occurrence analysis (Aria & Cuccurullo, 2017; Van Eck & Waltman, 2010).

Thus, this study will not only map the intellectual structure of the field but will also synthesize the main AI techniques applied in banking and the problems of their implementation.

Accordingly, this study seeks to answer the following research question: *What is the trend in scientific research on artificial intelligence in the banking industry, and which research trends, technologies, and future directions have emerged based on the latest scientific literature?*

To find the answers to these questions, the present paper aims at achieving four related goals. First, the article will study the development and scientific productivity of research on the application of AI in banking. Second, it will identify the journals, researchers, institutions, and countries that have contributed the most in terms to this field. Third, the article will investigate the conceptual architecture of the field by examining the key thematic clusters and AI technologies used in contemporary research on banking. Fourth, it will pinpoint the key areas for further investigation, technological challenges, and opportunities for the field.

The contribution of this paper to the existing literature is fourfold. First, the paper offers an up-to-date bibliometric review which focuses solely on the application of AI in banking rather than on finance in general as is the case in previous studies. Second, the study uses the combination of the capabilities of PRISMA, Bibliometrix, Biblioshiny, and VOSviewer to create a full map of research on the field in question. Lastly, it draws a link between bibliometric insights and banking practice using examples on how AI technology is used in detecting frauds, assessing credit risks, providing digital banking services, managing customer relationships, and complying with regulations (Van Eck & Waltman, 2010). Furthermore, the paper highlights some neglected areas of research and proposes a future research agenda in the areas of Explainable AI, Responsible AI, data governance, cybersecurity, and development of transparent and trustworthy intelligent banking systems. The rest of this paper is structured as follows. In Section 2, we provide a research methodology which includes the approach used in collecting data and bibliometric analysis carried out in this research. In Section 3, we present bibliometric results and thematic analysis. In Section 4, we highlight major applications of AI in banking. In Section 5, we discuss the challenges of adopting AI and identify future research areas. Finally, Section 6 contains conclusions drawn from this study along with its limitations and suggestions for future research.

2. Data and Method

This research involves a bibliometric analysis aimed at examining the evolution and present status of AI studies in the field of finance, specifically in the context of banking. The literature review procedure is conducted in accordance with the PRISMA 2020 protocol to guarantee the methodology of the work to be transparent, consistent, and replicable through the identification, screening, and eligibility phases (Fares et al., 2022). Bibliographic data has been acquired only from Scopus because of the database's multidisciplinary scope, high indexing standards, and detailed citation information, making it one of the most reputable sources for bibliometric analysis. The first step resulted in 191 articles according to the search query formulated as follows: TITLE-ABS-KEY (ai AND in AND financial AND institutions AND banks). Such an approach to literature search has been intentionally selected to obtain publications related to the

research purpose. Prior to the screening stage, 13 articles were eliminated based on pre-set criteria for search filters which include publication date (2020-2025), document type (article and conference paper), and language (English), thus leaving 178 articles suitable for title and abstract screening. In determining eligibility, each article was assessed in relation to inclusion and exclusion criteria. In total, 64 articles were excluded based on one or more of the following: irrelevance of the topic to the research focus (n = 24), inadequate thematic compatibility with the aims of the study (n = 18), unsuitable document type (n = 12), non-English language (n = 6), and inaccessible full text (n = 4). Therefore, 114 articles met the set eligibility criteria and were selected for the bibliometric analysis (Donthu et al., 2021). As illustrated in the PRISMA flow diagram, these **114** publications constitute the final dataset used to explore the scientific landscape of AI in banking. The subsequent bibliometric analysis examines publication trends, scientific collaboration, thematic evolution, and the principal application domains of AI, including fraud detection, anti-money laundering, credit risk assessment, explainable AI, and digital transformation. By combining a structured PRISMA-based selection procedure with the comprehensive coverage provided by the Scopus database, this study offers a robust overview of the intellectual development of AI research in banking while identifying the major research themes, emerging trends, and future challenges shaping this rapidly evolving field (Page et al., 2021).

Table 1. Reasons for Excluding Records During the Eligibility Stage

Reason for exclusion	Description	Number of records excluded (n)
Out of scope	Studies addressing AI without a specific focus on the banking sector	24
Insufficient thematic relevance	Studies not aligned with the objectives of the bibliometric review	18
Inappropriate document type	Conference papers, book chapters, editorials, reviews, or non-article publications	12
Non-English publications	Publications written in languages other than English	6
Full-text unavailable	Studies whose full text could not be accessed for eligibility assessment	4
Total excluded		64

Source: authors

Table 2. Main information of final records

Description	Results
Main information about data	
Timespan	2020 :2025
Sources (journals, books, etc)	96
Documents	114
Annual growth rate %	39,77
Document average age	1,81
Average citations per doc	7,895
References	3662
Document contents	
Keywords plus (id)	713
Author's keywords (de)	414
Authors	
Authors	394
Authors of single-authored docs	8
Authors collaboration	
Single-authored docs	8
Co-authors per document	3,61
International co-authorships %	21,05
Document types	
Article	50
Conference paper	64

Source: authors

Fig 1: Flowchart of the reviewed study

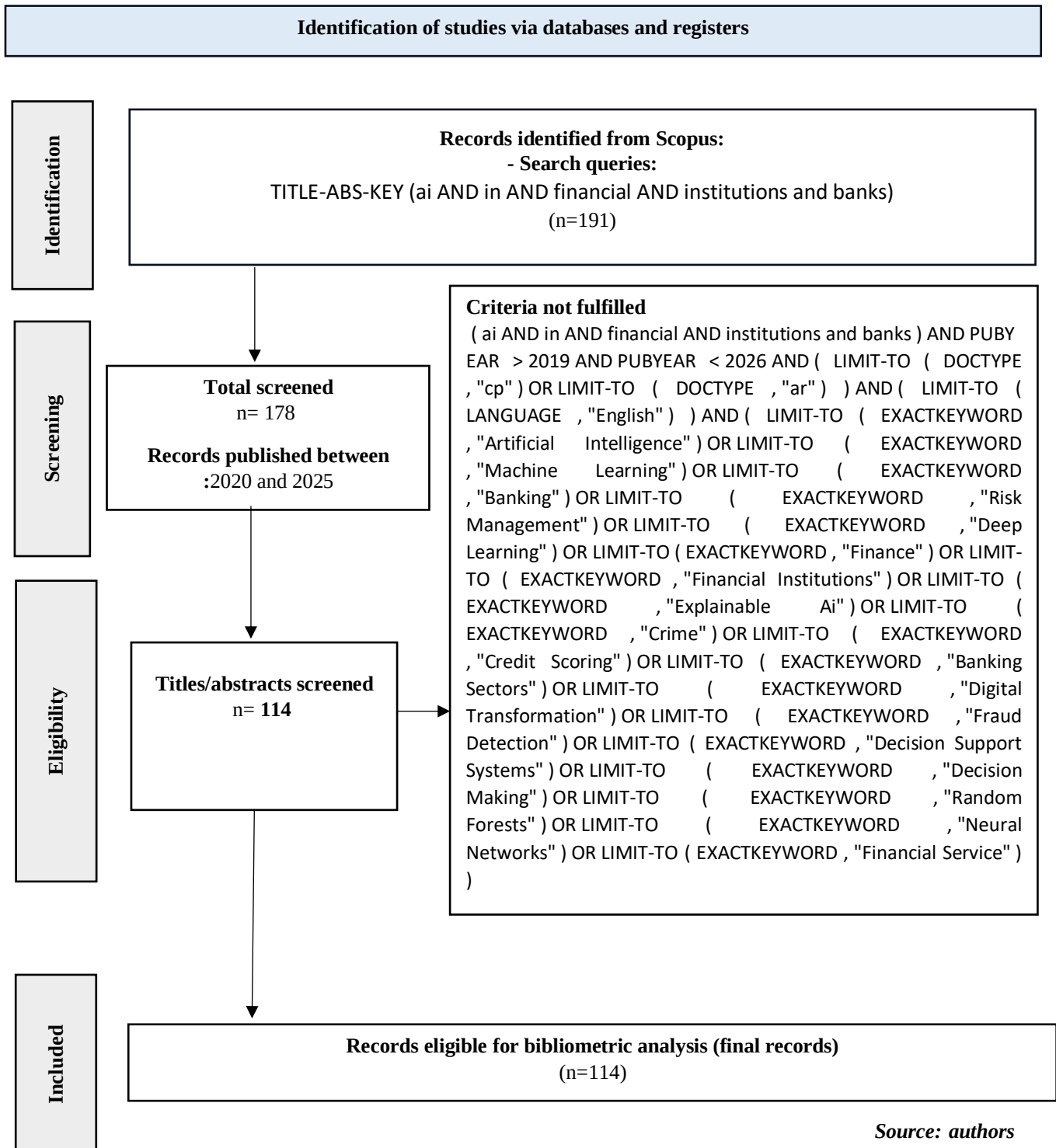


Table 2 presents a complete summary of the bibliometric analysis, covering 114 documents published between 2020 and 2025 in 96 diverse sources. The data indicates a notable annual growth rate of 39.77%, indicating a growing interest on the part of researchers. On average, documents are 1.81 years old and receive 7.89 citations, indicating the relevance of recent contributions. The dataset includes 394 authors, with an average of 3.61 co-authors per document and 21.05% of publications involving international collaborations. Most publications

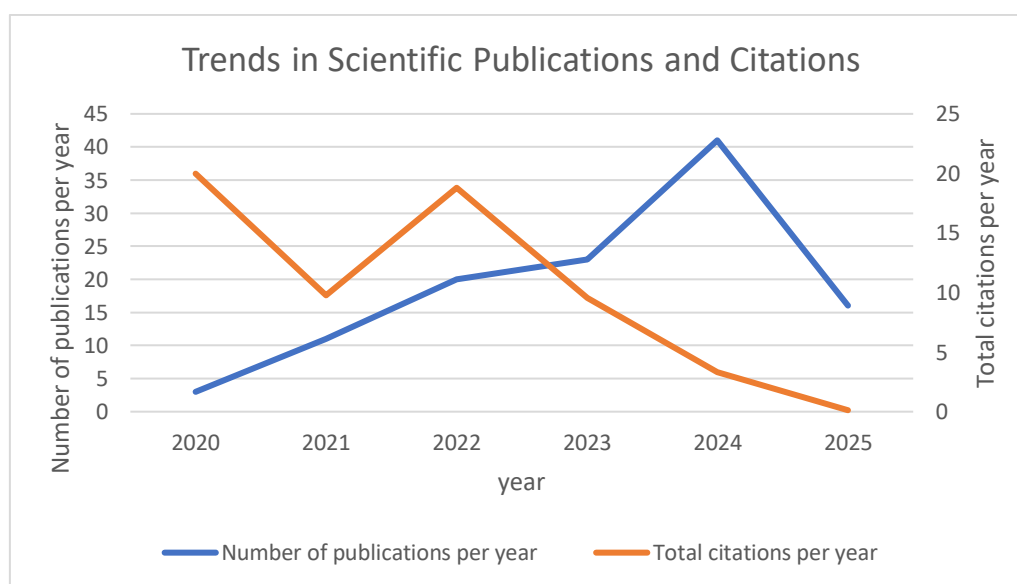
are conference papers (64), followed by journal articles (50), highlighting the dynamic and evolving nature of the subject.

3. Results

3.1 Trend in Scientific publications and citations (2020-2025)

An examination of the annual production of studies on AI applications in banking reveals a dynamic evolution between 2020 and 2025. As shown in Figure 2, the number of scientific publications steadily increased from 2020, starting with just 3 papers, and peaked in 2024 with 41 publications, indicating growing academic interest in the field. However, in 2025, the number of publications declined to 16, suggesting a potential shift in research focus or a maturing of the topic. In contrast, citation trends followed a different trajectory. Citations were highest in 2020 at 36, then declined overall despite a brief rise in 2022, before reaching a low of just 1 citation in 2025. The lower citation count observed for publications released in 2025 should be interpreted considering the temporal characteristics of citation accumulation rather than as evidence of declining scientific interest in the field. Since these studies have only recently entered the scientific literature, they have had limited time to be disseminated, recognized, and cited by the research community. This phenomenon, commonly referred to as the citation window effect, is an inherent characteristic of bibliometric analyses and frequently affects the citation performance of newly published works. Consequently, the observed decline in the number of citations for 2025 is an inevitable lag between the publication date and citation date but not any reduction in the number of research studies carried out or the saturation of artificial intelligence studies in banking research. The above hypothesis is also proved by the constantly growing number of scientific publications each year within the whole period of analysis.

Fig 2. Trends in publications and citations related to AI applications in bank.



Source: authors

3.2 Analysis of literature sources

Analysing the sources of literature is essential for identifying the most active publication venues in each field and for helping researchers target the most impactful platforms. The table above highlights the primary sources of articles related to AI applications in financial institutions. Lecture Notes in Networks and Systems emerges as the most prominent source, with 11 articles

Analysing the most active authors in a research domain provides valuable insight into the intellectual structure and leadership of the field. It helps identify key contributors and potential collaborators while also revealing patterns in publication output. The figure above highlights the most relevant authors in AI-related research applied to banks. Vladlena Benson and Mustafa Raza Rabbani emerge as the most prolific authors, each with three publications, indicating their strong engagement and leadership in this area of study. They are followed by a group of authors Bogdan Adamyk, Ranjana Agrawal, Anurag Banerjee, Robert Brooks, Tom Butler, Heloisa Candello, Rogerio De Paula, and Sharmishta Desai each contributing two publications. While they have slightly fewer publications, their consistent contributions demonstrate a solid involvement in the field (Ahmadi, 2024). This distribution reflects a collaborative and diverse research landscape, where several individuals contribute regularly to advancing knowledge on AI applications in finance. The presence of multiple authors with similar publications suggests a decentralized landscape, highlighting the importance of diverse contributions in shaping ongoing research.

3.3.2 Relevant affiliations and countries/regions

The figure displays the top 10 most relevant institutional affiliations in AI related research within the financial sector, ranked by the number of articles published (Costagliola et al., 2018). Dr. Vishwanath Karad MIT World Peace University leads the list with 10 published articles, indicating a strong institutional focus on advancing AI applications in finance. Aston University follows closely with 8 publications, reflecting its active involvement and consistent output in the field. Both institutions appear to play a leading role in shaping research directions and contributing to the growing body of knowledge in this area.

Next in line are Hajee Mohammad Danesh Science and Technology University and Yeshwantrao Chavan College of Engineering, each contributing 5 publications. Their steady research activity demonstrates their commitment to exploring AI solutions in financial contexts. A group of institutions including FR. Conceicao Rodrigues College of Engineering, Jazan University, Lake Forest College, MLR Institute of Technology, The Hashemite University, and VIT Bhopal University each produced 4 articles, indicating a broad base of institutional participation across different regions.

This distribution highlights a diverse and collaborative research environment, where both large and emerging institutions contribute meaningfully to the field. It emphasizes the global nature of AI research in finance and underscores the importance of institutional support and international academic engagement in advancing innovation and knowledge-sharing within the sector.

Fig 4. The 10 leading affiliations in ai research within Banks.



Source: authors

As a result of the analysis of co-occurrences between keywords, six related thematic groups were found which jointly encompass all major research directions that define the development of artificial intelligence in the banking industry. Far from being independent research directions, those groups reflect the gradual development of scientific research towards solving problems faced by contemporary banks at the levels of technology, operation, and regulation. The interconnected nature of those groups is indicative of the way AI research has moved from being algorithm-based to a wider multidisciplinary field, where technology is intertwined with finance and regulation.

The **red cluster** deals with the topic of artificial intelligence and its use in finance and fintech. It has significant terms such as "finance," "financial institution," "deep learning," "big data," and "Internet of Things," reflecting a concentration on the way new technologies are changing financial services and markets. The cluster suggests great interest in how AI can be utilized to enhance financial performance, automate processes, and facilitate improved decision-making in banking and investing.

The **green cluster** is interested in machine learning, risk management, and fraud detection. Some of the key words in this cluster are "cybersecurity," "neural networks," "random forest," "support vector machines," and "learning algorithms." This word cluster centers on the development of intelligent systems designed to detect fraud and manage risk through the observation of real-time transactions and predictive modeling.

Blue cluster emphasizes customer experience and banking services, with terms like "banking," "sales," "decentralized finance," and "decision-making." Blue cluster suggests research exploring how AI transforms traditional banking operations and improves customer interactions, efficiency, and trust in online services.

The **yellow cluster** is associated with financial institutions, fraud detection, and finance-related applications, with terms like "finance," "fraud detection," and "financial institutions." This cluster suggests a merge between operational finance and regulatory settings where AI is utilized to serve compliance purposes and protect institutional integrity.

The **light blue cluster** targets user experience and ethics, e.g., terms such as "customer experience," "chatbots," and "ethical considerations." This reflects greater acknowledgement of human and ethical dimensions of AI use in finance, specifically concerning transparency, trust, and customer-consumer interaction with automated systems.

The **purple cluster** also contains keywords for advanced modeling techniques and predictive analytics such as "logistic regression," "decision trees," and "performance." They pertain to research focused on enhancing algorithmic models towards greater accuracy and decision support in financial applications.

In sum, the six thematic clusters provide an appropriate depiction of the conceptual framework of artificial intelligence studies in the banking industry and directly contribute to the aims of the current research. In general, all these themes demonstrate a clear trend in scientific literature shifting from algorithm design in artificial intelligence to a new scientific agenda devoted to the application of these algorithms in banks and banking decision-making. The significance of the themes of machine learning, fraud detection, risk management, cybersecurity, and financial decision support proves the key role of artificial intelligence technologies in improving financial security and fighting modern financial crimes. However, at the same time, the rise of themes like digital banking, customer experience, predictive analytics, and explainable artificial intelligence shows the growing scope of artificial intelligence in enhancing banking performance. This diversity of thematic topics shows that the field of AI research is getting more mature since, at the initial stage of its development, AI was considered primarily as an instrument while now as a strategic means of transforming banks through digitalization. As such, not only does the revealed structure of topics reflect the organization of scientific

knowledge on AI in the banking context but also reveal the evolution of research priorities in the face of technological, operational, and regulatory challenges in modern banking. This makes it possible to gain insight into the direction of AI research in banking and helps identify the trends that will drive academic research and practice in the future. In conclusion, keyword co-occurrence analysis shows that AI research in banking has undergone a continuous transition from being purely technology-based to a multidisciplinary field addressing various problems of banking. The thematic clusters revealed show that the field of research has expanded from merely developing algorithms to their application in different areas, including fraud detection, risk management, cybersecurity, customer-oriented services, explainable AI, and regulatory compliance. It is because of the growing application of intelligent technologies in the functioning of banks. It also shows how research interests have been broadened by considering both innovative solutions provided by technology and the needs of organizations. Thus, the thematic structure obtained from the bibliometric analysis enables us to understand the development of AI research in the banking industry and determine the key technological trends and issues that will determine the future research and practices in banking.

4. Overview

4.1 AI Research Trends Across Banking Activities

The results obtained during bibliometric analysis demonstrate that banking services are among the key application areas of artificial intelligence research, emphasizing the growing importance of intelligent technologies in the processes of bank operations. In particular, the thematic clusters and the co-occurrence network of keywords illustrate a distinct shift from purely algorithm-based research to the study of problems related to real-world banking and its business applications. The problems of fraud detection, credit risk evaluation, payment systems, customer relationship management, asset management, and digital banking become the primary research subjects, illustrating the growing involvement of AI technologies in improving the efficiency and security of banks' activities. This demonstrates that artificial intelligence is no longer seen as an enabling technology but as an essential element of banking innovation and digitalization. On this basis, this section discusses the main banking services where the use of these AI technologies is applied. They include numerous financial institutions that manage deposits, loans, foreign exchange transactions, asset management, and other financial services. This sector plays a vital role in the economy by facilitating capital movement, ensuring liquidity, and providing financing mechanisms for individuals, companies, and governments. It primarily consists of commercial banks, investment banks, central banks, and credit cooperatives (Königstorfer & Thalmann, 2020). Commercial banks process customer deposits and loans, while investment banks focus on financial markets, handling mergers and acquisitions, securities issuance, and financial advisory services. The rise of digital banks and fintechs is transforming traditional banking methods (Königstorfer & Thalmann, 2020). Central banks, such as the European Central Bank (ECB) and the United States Federal Reserve (FED), regulate currency and oversee the banking system to maintain economic stability (Xu et al., 2021). By financing business investments and growth while managing financial risks through various products and services, the banking sector actively drives economic development.

4.2 Banking Context of AI Adoption

From the perspective of the bibliometric analysis, one should note that the application of AI in banking has gradually covered diverse types of financial institutions, thus showing the integration of intelligent technology in the banking sector. It should be emphasized that the literature review suggests that retail, commercial, investment, and digital banks participate in the investigation of AI technologies, even though the goals and approaches differ in each

institution. However, regardless of the differences between the institutions, the use of AI allows for the improvement of operational efficiency, customer engagement, financial security, and the implementation of the necessary regulations. As a result, it is vital to consider the variety of banking institutions when analysing the identified themes through the bibliometric analysis because it allows for understanding the challenges faced by researchers when conducting research in the sphere. The information provided in Table 4 demonstrates the diversity of institutions within the banking sector and their role in the economy.

Table 4. Diverse institutions in the Banking sector

Commercial Banks	Commercial banks, the most widespread financial institutions, provide individuals, companies, and organizations with a wide range of services (Königstorfer & Thalmann, 2020). They manage checking and savings accounts, facilitate payments, and issue loans for personal, commercial, and industrial needs. Their role is vital to economic stability, as they enable daily financial transactions, support small and medium-sized enterprises (SMEs) with credit lines, and regulate cash flow through treasury services (Xu et al., 2021).
Investment Banks	Investment banks operate differently from commercial banks because they do not manage public deposits. Instead, they specialize in advanced financial activities, including issuing securities, advising on mergers and acquisitions, and managing portfolios for large companies and governments. They facilitate capital access for major enterprises (McKillop et al., 2020 ; Bergendahl, 1993), support financial market transactions, and enhance market stability by creating innovative financial products.
Development Banks	Development banks play a clear strategic role in the landscape of public and specialized financial institutions. They implement public policies by providing targeted financial support for development projects. Often called Public Development Banks (PDBs) or Development Financial Institutions (DFIs), these banks focus on long-term financing for key sectors such as infrastructure, industry, and agriculture (Goddard et al., 2007; Guille, 1994) In regions where financial markets remain underdeveloped, they actively bridge financing gaps. By injecting capital into critical projects, they drive economic growth, reduce regional disparities, and promote more balanced and sustainable development.
Cooperative Banks	Cooperative banks emerged to meet the financing needs of low-income households. Initially structured as privately owned entities, they established principles that set them apart from traditional corporation services (Xu et al., 2021). One key principle, "one member, one vote ," ensures that each member, known as a sociétaire, actively participates in governance. Another fundamental concept, "dual status," gives members a dual role as both co-owners and customers, reinforcing their central position within the cooperative and mutualist model. Their democratic governance structure allows them to adapt to local needs effectively, ensuring a more responsive and sustainable banking model (Joly, 2013); Ben Slimane et al., 2017).

Source: authors

4.3 banks services

Banks do much more than handle deposits and issue loans. They provide a wide range of financial services that keep the economy running smoothly.

- **Deposit Management**

Table 5 shows that managing deposits is a fundamental role of banks, which offer diverse types of accounts:

Table 5. Various Deposit Management

Current Accounts	These accounts allow customers to deposit and withdraw money at any time, making them ideal for daily transactions such as bill payments and purchases. Banks often provide additional services, including checks, debit cards, and ATM access, ensuring convenience and financial flexibility (Königstorfer & Thalmann, 2020).
Savings Accounts	Savings accounts help customers grow their funds through earned interest. Banks typically hold these deposits for extended periods, allowing for steady financial growth. They adjust interest rates based on banking policies and market conditions, making savings accounts a vital tool for long-term financial planning (Fox & Van Droogenbroeck, 2018).

Term Accounts	Also known as term deposit accounts, these accounts offer higher interest rates in exchange for a commitment to keep funds deposited for a fixed period. Withdrawing funds before maturity generally incurs penalties (Fox & Van Droogenbroeck, 2018).
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Source: authors

Banks pool these deposits to secure stable funding, which they use to finance loans, ensuring a balanced and efficient financial system.

- **Credit Allocation**

Table 6 shows that banks play a fundamental role in granting loans and providing funds to individuals, companies, and governments. The main types of loans include:

Table 6. Various Credit Allocation

Personal Loans	Individuals use these loans to finance personal expenses such as vehicle purchases, education, or personal projects. Banks set fixed repayment terms and predetermined interest rates for these loans (Guille, 1994).
Mortgage Loans	Banks design these long-term loans specifically for real estate purchases. They can extend up to 30 years and are secured by the acquired property (Guille, 1994).
Business Credit	Banks provide these loans to help companies sustain operations, expand, or meet other financial needs. They offer business credit in the form of credit lines, term loans, or project-specific financing (Königstorfer & Thalmann, 2020).
Credit Cards	Credit cards enable customers to borrow money up to a predefined limit for purchases. Borrowers must repay the used amount and often incur interest if they do not pay the full balance each month (Novakovic & Markovic, 2020; Jomon Jose & Aithal, 2023).

Source: authors

Banks generate revenue from these credit activities through interest and fees while driving economic growth by encouraging investment and consumer spending.

- **Payment Services**

Table 7 shows that payment services play a significant role in facilitating financial transactions in the entire economy. Banks provide a range of payment solutions, including:

Table 7. Various Payment Services

Checks	Customers make payments by issuing a written payment order. Although electronic payments have reduced their use, checks remain relevant, especially in commercial transactions (Königstorfer & Thalmann, 2020).
Debit and Credit Cards	Customers use debit cards to make purchases directly from their bank accounts, while credit cards allow them to borrow funds for purchases with deferred repayment (Königstorfer & Thalmann, 2020; Assef & Steiner, 2020).
Bank Transfers	Banks transfer funds between accounts both nationally and internationally. Individuals and businesses commonly use electronic transfers for bill payments, salary disbursements, and various financial transactions (Le Buzulier, 2019).
Online Payment Systems	As e-commerce grows, banks develop secure online payment solutions for purchasing goods and services over the Internet. They provide digital wallets and mobile payment systems , enhancing convenience and transaction security (Königstorfer & Thalmann, 2020).

Source: authors

These services play an essential role in streamlining economic transactions, enabling fast and secure payments while strengthening the digital economy.

- **Asset Management Services**

Table 8 shows that banks provide asset management services to help customers invest their money efficiently.

Table 8. Diverse Asset Management Services

Investment Advice	Banks deliver personalized recommendations on investment options, including stocks, bonds, mutual funds, and other financial instruments. They tailor these recommendations to match the customer's risk profile, financial objectives, and market conditions, ensuring a strategic and informed investment approach (Joly, 2013).
Portfolio Management	For individuals and institutions with high net assets, banks offer portfolio management services where professional fund managers make investment decisions to maximize returns while minimizing risks (Joly, 2013).
Complex Financial Products	Banks design and market advanced financial instruments, such as derivatives, which customers use to manage financial risks or speculate on market fluctuations (Joly, 2013).

Source: authors

These services help banks generate additional income and actively support customers in achieving their financial objectives through strategic investment solutions.

- **Digital Services and e-Banking**

Table 9 shows that with the advent of digital technologies, banks have developed a wide range of online services to meet the evolving needs of modern customers.

Table 9. Diverse Digital Services and e-Banking

Online Banking	Customers manage their accounts, transfer funds, pay bills, and monitor their finances through bank websites or mobile applications, enjoying convenience and real-time access to their financial information (Angelakopoulos & Mihiotis, 2011).
Mobile Payments	Banks enable customers to make payments directly from their smartphones using mobile payment applications. Customers transfer money peer-to-peer, make in-store purchases, and pay invoices securely and efficiently through these platforms (Khurana, 2020; Le Buzullier, 2019).
Digital Security	Banks invest heavily in robust security measures to protect sensitive customer data. They implement tools such as two-factor authentication, data encryption, and transaction monitoring systems to identify and prevent suspicious activities, ensuring the integrity of financial transactions (Angelakopoulos & Mihiotis, 2011).
Online Customer Support	Banks provide customer support through digital platforms, enabling customers to solve problems, ask questions, and receive assistance without visiting a branch. This approach enhances accessibility and convenience, meeting the demands of an increasingly connected world. These digital services not only enhance the customer experience but also reduce operating costs and help banks remain competitive in an increasingly digital environment (Khurana, 2020; Angelakopoulos & Mihiotis, 2011).

Source: authors

Banking services, diverse and constantly evolving, meet traditional customer needs while adapting to the demands of an increasingly interconnected economic landscape. Understanding the wide range of services banks offer highlights their essential role in supporting economic activities and facilitating daily transactions. AS banks continuously adapt to technological innovations and shifting consumer expectations, they maintain their relevance and strategic importance, securing their role as a cornerstone of the future economy.

5. AI Techniques Emerging from the Bibliometric Analysis

From the perspective of bibliometric analysis, one can see that machine learning and intelligent predictive models represent the essential technological basis of modern AI research in banking. It is proved by the significant presence of these techniques in thematic clusters and co-occurrences of keywords. It is obvious that they are the keyways to solve various issues related to different banking applications, such as fraud detection, credit risk, AML, customer behavior analysis, and decision support in finance. Such results show the tendency in literature towards the development of new approaches which make it possible to increase the efficiency and precision of operations in banking institutions. In other words, such AI models are not

considered to be just computing approaches but strategic tools that facilitate digital transformation and innovation processes in conditions of increasing complexity of regulations. Based on the results of the bibliometric analysis, the next section will discuss the main AI models in literature.

Random Forest algorithms play a key role in identifying suspicious patterns within digital transactions. In banking, they are used to scan large sets of payment data to detect inconsistencies that may indicate fraudulent activity. By automating the detection of these anomalies, banks enhance the speed and accuracy of their fraud prevention systems and reduce reliance on manual oversight (Königstorfer & Thalmann, 2020).

Artificial Neural Networks (ANN) are well-suited to uncover complex, hidden relationships in financial data. These models are particularly effective at detecting abnormal behaviours that might signal fraud, especially in electronic payment systems. They are also employed to improve credit scoring by learning from historical lending outcomes and customer behaviour patterns (Abi, 2025 ; Abellán & Castellano, 2017) .

Support Vector Machines (SVM) are used in scenarios where high-dimensional data must be interpreted accurately like in classifying customer risk profiles or flagging unusual transactions. They are particularly valuable in distinguishing high-risk clients from low-risk ones, contributing directly to fraud prevention in credit assessments (Abellán & Castellano, 2017).

Clustering algorithms, which operate without predefined labels, help banks segment their customers based on behavioural patterns. These groupings can reveal outlier clients who deviate from the norm which often point to risky or potentially fraudulent activity. In doing so, these models support personalized marketing and fraud monitoring simultaneously (Jain, 2025; Königstorfer & Thalmann, 2020).

Probabilistic decision trees (CDT) are specifically designed to manage uncertainty in financial data. They outperform standard models when it comes to reducing classification errors in ambiguous cases. In banking, they are especially useful in improving credit risk assessments, offering more reliable evaluations of customer credibility, and minimizing financial loss due to misjudged loans (Abellán & Castellano, 2017).

Ensemble methods like Bagging, AdaBoost, and Random Subspace combine several classifiers to boost performance. In fraud detection systems, they reduce false positives and enhance prediction stability by balancing the strengths and weaknesses of individual models. This approach makes fraud detection more robust in the face of diverse transaction behaviours (Abellán & Castellano, 2017; Novakovic & Markovic, 2020).

Robo-advisors, though not directly detecting fraud, indirectly support financial integrity by offering fully automated, personalized investment strategies. By analysing financial profiles, risk tolerance, and investment goals, they streamline portfolio management. Their structured and traceable decision processes also make unusual investment behaviours more visible and easier to flag (Jomon Jose & Aithal, 2023).

Natural Language Processing (NLP) models analyse client communication like chat messages or service requests to detect inconsistencies or red flags in language use. In banking, NLP is embedded in chatbots and customer service platforms, where it helps automate responses while monitoring for possible signs of social engineering or attempted fraud (Königstorfer & Thalmann, 2020).

Predictive analytics enables banks to anticipate fraudulent behaviours by identifying trends and behavioural signals in advance. These models are also used to forecast credit defaults and assess future customer risk, allowing institutions to intervene before losses occur. In fraud detection, this foresight strengthens a bank's ability to take pre-emptive action (Jomon Jose & Aithal, 2023; Abi, 2025).

Genetic algorithms and **Particle Swarm Optimization (PSO)** are used not for direct fraud detection, but for strategic planning in banking infrastructure. For example, they help determine

the best locations for ATMs and branches based on customer activity and geographic data. By the placement of physical resources, they help reduce fraud risks associated with poorly managed service distribution (Königstorfer & Thalmann, 2020).

Chatbots, powered by AI, automate customer support around the clock. While their main function is service delivery, they also serve a protective role by overseeing routine queries and filtering suspicious requests. This minimizes human error, enhances operational efficiency, and provides an early defense against fraud attempts through social interaction (Abellán & Castellano, 2017).

Real-time network traffic monitoring, enabled by AI, serves as a frontline defense against cyber threats. In banking environments, these systems detect, alert, and sometimes block suspicious digital activities before they escalate. By proactively managing security at the infrastructure level, they protect sensitive customer data and maintain system integrity against digital fraud (Jomon Jose & Aithal, 2023).

6. Strategic Implications of AI Adoption

SWOT analysis is a result of the expansion of the conclusions drawn from the bibliometric analysis to draw strategic conclusions about the current situation regarding the implementation of AI in the banking industry. Based on the findings of the science mapping analysis, including the identification of thematic clusters and the prevailing directions in the scientific research, the SWOT analysis reflects the main findings of the literature and interprets them in terms of their strategic implications for management. SWOT analysis is not an independent tool but rather complements the results of the bibliometric analysis and helps link technological developments with the opportunities and threats faced by financial organizations. The rise of Artificial Intelligence (AI) is profoundly transforming the banking sector, particularly in the areas of fraud detection and prevention. This SWOT examines the main **strengths**, **weaknesses**, **opportunities**, and **threats** associated with the integration of AI technologies in highly regulated financial environments.

Table 10. Strengths

Aspect	Description
High Fraud Detection Capability	AI models such as Neural Networks, Random Forests, and Support Vector Machines (SVM) are particularly effective in identifying complex fraud patterns that often evade traditional systems.
Process Automation	The adoption of AI-powered tools like RegTech, chatbots, and robo-advisors significantly reduces operational burden while improving responsiveness to fraud threats.
Data-Driven Decision-Making	Predictive analytics and ensemble models enhance credit risk evaluation and facilitate faster, more objective decisions.
Adaptive Learning	AI algorithms continuously learn from historical data, progressively improving their accuracy and ability to detect emerging fraud schemes.
Personalized Services	Through techniques such as clustering and behavioral segmentation, AI enables personalized financial services and the early detection of anomalous behavior linked to fraud.

Source: authors

Table 11. Weaknesses

Aspect	Description
Lack of Interpretability	Advanced models, particularly deep neural networks and ensemble techniques, often function as “black boxes,” limiting transparency and regulatory explainability.
Data Quality Dependency	Model performance is highly contingent on the availability of large, clean, and well-labeled datasets. Poor data governance compromises accuracy.
Sensitivity to Class Imbalance	Algorithms like decision trees and SVMs may perform poorly when fraudulent transactions are underrepresented, leading to false positives or missed fraud cases.

Infrastructure Demands	Real-time fraud detection systems require robust computing infrastructure, including high-performance servers and scalable storage solutions.
Organizational Resistance	Introducing AI often involves significant internal change management. As shown in the case of Sberbank, employees may resist due to inadequate training or mistrust in automation.

Source: authors

Table 12. Opportunities

Aspect	Description
Enhanced Regulatory Compliance via RegTech	AI facilitates the automation of regulatory reporting and auditing, significantly lowering compliance costs and increasing audit efficiency.
Real-Time Fraud Detection	Integration with real-time monitoring systems allows for instant alerts, voice authentication, and proactive fraud mitigation.
Scalability Through Cloud Infrastructure	Leveraging cloud platforms and data lakes improves the scalability of AI systems and accelerates model training and deployment.
Improved Customer Experience	AI-driven conversational agents, combined with behavioral analytics, deliver highly personalized client interactions and help detect unusual financial activity.
Geospatial Optimization	Advanced algorithms such as genetic models and particle swarm optimization (PSO) support strategic decisions like ATM placement to mitigate fraud risks.

Source: authors

Table 13. Threats

Aspect	Description
Cybersecurity Vulnerabilities	Despite being used to detect threats, AI systems are themselves susceptible to adversarial attacks and system breaches, jeopardizing reliability and data privacy.
Ethical and Legal Concerns	Automated decisions and opaque algorithms raise critical issues around bias, fairness, and accountability, particularly in loan approvals or account restrictions.
Overreliance on Automation	Excessive dependence on AI may reduce human oversight, making it more difficult to detect novel or unexpected fraud tactics.
Customer Reluctance	Certain customer segments may be skeptical of AI-managed financial services, especially in high-stakes areas like investment advising or loan decisions.
Model Drift	Without periodic retraining, AI models risk becoming outdated as fraud techniques evolve, leading to diminished detection performance over time.

Source: authors

7. Discussion

Artificial Intelligence (AI) has become a strategic cornerstone of the digital transformation of the banking sector. The findings of bibliometric analysis present a complete picture of the development of AI research in banking, forming an analytical background for the discussion below. An annual scientific growth rate of 39.77% is indicative of a growing interest in academia in innovative solutions in the field of AI banking, which indicates the necessity to consider the growing significance of smart technology to solve various challenges faced by contemporary financial organizations. Also, the distribution of scientific works among the leading countries, prominent scholars, and research collaborations reveals that the field of AI in banking represents a dynamically developing multidisciplinary area with a high degree of international collaboration. Keyword co-occurrence analysis and thematic clustering additionally show that issues such as machine learning, fraud prevention, financial risk management, digital banking, cyber security, and customer-based financial services represent the main directions of current research. All these together suggest an evident trend away from technologically focused studies to application-related studies that consider the role of integrating artificial intelligence into fundamental bank operations and decision support systems. With these observations in mind, the next section is devoted to analyzing the relevance of these studies and their implications for further development of AI in the banking industry. As financial crimes like money laundering get increasingly sophisticated and complex, traditional detection methods are no longer sufficient. Financial institutions are thus compelled

to introduce clever systems that could scan in real-time, precisely detect outliers, and make data-driven decisions promptly (Jomon Jose & Aithal, 2023). AI solutions address these requirements by scanning huge amounts of transactional data, learning automatically, and constantly evolving to keep pace with changing fraudulent patterns. Two of the most effective AI methods are machine learning and deep learning. Machine learning allows systems to learn from existing data without manual programming, and it is thus able to identify complex patterns of fraud that might otherwise go unnoticed (Bello & Olufemi, 2024; Khurana, 2020). Deep learning takes it a notch higher with automatic learning of features and application of multilayer neural networks to model highly nonlinear relationships. Such advanced models work best at detecting subtle or well-hidden fraud attacks because they can tap even the slightest deviation in user or transactional patterns (Bello & Olufemi, 2024; Khurana, 2020). Greater deployment of AI in banking is intertwined with the plethora of problems the sector is experiencing. The hyper growth in online commerce, the explosion in data volumes, the relentless evolution of regulatory regimes, and the proliferation of fraud techniques all necessitate an ever more agile and astute response. From work by Florian Königstorfer and Stefan Thalmann, it is possible to see how business banks are leveraging AI to enhance customer experience and maximize operational effectiveness above traditional information systems. These are enhanced by the ability of AI to automate complex tasks, reduce the workload of man, and enable quicker decision-making (Maple et al., 2023). AI performance is also seen in regional banking revolutions. For example, Jomon Jose M. and P. S. Aithal's study on India's public sector banks in Kerala highlights how AI technologies like chatbots, automated advisory services, credit scoring solutions, and AI-based cybersecurity are transforming banking operations, security, and the customer experience. Innovations demonstrate that even traditional organizations can gain significant competitive advantage with AI adoption (Jomon Jose & Aithal, 2023). Though AI is used, it has its challenges. From the findings of the bibliometric analysis, it is evident that machine learning and deep learning continue to dominate AI research in the banking industry, which clearly illustrates the significance of these methods in the use cases of fraud detection, credit scoring, money laundering, and financial risk management. Nevertheless, there have been certain changes in the emerging themes from the analysis of relevant literature, as the focus of research has become increasingly concerned with the restrictions that arise when using these technologies. The recent literature is increasingly oriented towards such issues as model explainability, training data, algorithmic bias, and AI governance in the banking industry. These problems are particularly relevant for decision-intensive use cases when the dependability and accountability of AI-based suggestions become highly relevant for regulatory compliance, business sustainability, and trustful relationships with clients. This shift in the focus of studies proves that science becomes more balanced and realizes that to implement AI solutions successfully in the banking industry, apart from predictive power, we need to develop reliable and trustworthy AI. One of the biggest issues is the limited interpretability of certain models, especially deep neural networks, because they are usually considered "black boxes." This lack of transparency poses a regulatory challenge, especially when the decisions made by AI-based systems are sensitive, like rejecting an application for a loan or freezing an account. In addition, the validity of AI models also largely relies on the quality and integrity of data. Poorly formatted or biased data can lead to improper predictions and skewed decisions. Infrastructural inputs for feeding real-time AI systems are also technology and capital-intensive. SWOT analysis here highlights not only the weak and strong areas of AI adoption but also its tremendous opportunities. One such chance is the use of RegTech tools to automate regulatory compliance, which simplifies reporting and auditing processes, lowers operational expenses, as well as error rates (Olaiya et al., 2024). Further, the combination of AI with cloud platforms and data lakes makes it possible for scalable deployment and continuous model improvement by drawing from big and varied data sets (Jarrahi, 2018). Geospatial optimization models, for instance, can assist

banks in determining the optimal locations to install ATMs, thereby avoiding the physical threat of fraud. However, there are emerging types of threats being introduced by AI systems. They may be vulnerable to adversarial attacks, whereby criminals exploit vulnerabilities in models to direct outcomes. Excessive automation can also lower human oversight, potentially allowing new types of fraud to go undetected. Resistance from customers is also an issue, especially from those who are concerned about fully automated financial decision-making (Jomon Jose & Aithal, 2023). Finally, the reduction in model performance over time because of changes in fraud patterns is an important issue, requiring repeated retraining to remain current and precise. The application of AI in anti-money laundering and fraud detection is a paradigm shift for the banking industry. These technologies offer unprecedented precision, adaptability, and reactivity, superior to those of traditional systems. Yet for them to deliver their maximum value, banks must develop solid governance constructs, ensure algorithmic transparency, and make investments in employee reskilling. Used responsibly and with strategy, AI is not just a successful defense against financial crime, but also an enabler of future innovation, productivity, and sustainable trust in the future of finance (Maple et al., 2023).

8. Conclusion

From the results of this bibliometric study, one gets an insight into the development of scientific studies regarding the application of artificial intelligence in the banking industry. Based on a sample of 114 scientific works published in the Scopus database from 2020 to 2025, it can be noted that there is a high growth rate of AI-related studies in the banking industry (39.77%). Also, from this bibliometric investigation, the top nations, scientists, and collaboration networks that drive scientific studies have been identified. Finally, the results of science mapping, such as keyword co-occurrence and thematic clustering, show that there are six major research streams in this field related to machine learning, fraud detection, financial risk management, digital banking, cybersecurity, and customer-oriented financial services. Overall, the data obtained proves that the studies related to the application of artificial intelligence in the banking industry have become quite developed. Application of Artificial Intelligence in Banking is a paradigm shift to the method of combating fraud, money laundering, and operational inefficiencies. With its ability to handle vast volumes of data, uncover concealed patterns, and adapt to novel threats, AI has been identified as a valuable tool in combating financial crime (Jain, 2025). Its benefits more accurate and automated and improved customer interaction are substantial. However, they are accompanied by critical challenges, primarily in the areas of model transparency, data stewardship, technological infrastructure, and public trust. To capture the maximum potential of AI, banks must balance innovation and compliance with ethical and regulatory expectations in a fine manner. To achieve so, they must establish robust governance frameworks, engage in explainable and transparent AI and unbiased algorithms, and foster a culture of ongoing learning and technological progress (Novakovic & Markovic, 2020). Even though the current study presents a solid bibliometric analysis of the development of AI research in the banking industry, it should be noted that the results obtained should be considered with a few methodological flaws. First, it relates to the use of a single Scopus database as the source of bibliometric data. Despite the comprehensive disciplinary coverage and the accuracy of citation data provided by Scopus, the use of only one database may have narrowed the selection of literature sources that are not available in Scopus but are found in Web of Science or Google Scholar. Second, it relates to the timeframe of the review itself, which is limited to the publications published from 2020 to 2025. Moreover, even though the identification, screening, and eligibility phases of the review were performed following the PRISMA 2020 guidelines using clear selection criteria, no formal evaluation of the inter-rater agreement was carried out during the review process. The limitations of the study may be addressed in future bibliometric analyses by using various scientific databases and expanding

the time horizon while applying the peer review process to validate results obtained through the bibliometric analysis to increase the accuracy, reproducibility, and transparency of the study. Bibliometric analysis revealed some areas of research which currently receive relatively low attention but have significant importance in terms of further research in the field. Although the existing literature has primarily concentrated on machine learning, fraud detection, anti-money laundering, and financial risk management, the thematic analysis showed that explainable artificial intelligence (XAI), responsible AI, federated learning, AI governance, privacy enhancing technologies, and trustworthy intelligent decision support systems have not been paid sufficient attention to in terms of their implementation in the banking industry. Future research needs to focus on these relatively untouched topics to create AI systems which have excellent predictive power in combination with fairness, transparency, resilience, and responsible deployment. Investigating these lines of research will not only help to fill in the research voids highlighted by the current bibliometric study but will also lead to the development of more secure and sustainable AI-driven banking systems. In the future, new technologies such as federated learning, quantum computing, and advanced natural language processing will keep on refining fraud detection, real-time compliance, and customer personalization (Jomon Jose & Aithal, 2023). Furthermore, collaboration between regulators and financial institutions will be critical in defining open, responsible, and adaptable AI governance models. As technologies continue to advance, banks that strategically invest in AI research, ethics-driven deployment, and cross-industry partnerships will be in the best position to facilitate the movement towards an even more secure, intelligent, and inclusive financial ecosystem (Pazarbasioglu et al., 2020).

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