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Latest Trends in the Use of Artificial Intelligence in the Banking Sector

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The study examines the latest trends in the application of artificial intelligence (AI) in the banking sector, with a focus on bank failure prediction, risk management and customer relationship optimisation. The research is based on a systematic literature search of relevant publications in the Scopus and Web of Science databases, using the PRISMA methodology for source selection and analysis. The results show that Unsupervised Learning Models dominate in bankruptcy prediction and risk analysis, while Natural Language Processing and Deep Learning techniques are mainly focused on improving customer relationships and increasing bank efficiency. The research shows that AI is playing an increasingly important role in banking decision-making, but that the different application areas face different regulatory and ethical challenges. The results underline the importance for financial institutions to improve the transparency and interpretability of AI and to develop adaptive regulatory frameworks to balance innovation and security.

Journal of Economic Literature (JEL) codes: C10, G21, O33

Keywords: artificial intelligence, banking sector, financial services, trend analysis

1. Introduction

Artificial intelligence is playing an increasingly important role in the banking sector, revolutionising the areas of credit scoring, risk analysis and transaction processing. The use of AI-based systems enables automated decision-making, more accurate forecasting of financial risks and the development of improved fraud detection mechanisms. Financial institutions are increasingly taking advantage of the opportunities offered by Machine Learning and data science to help improve the efficiency of the sector.

* The papers in this issue contain the views of the authors which are not necessarily the same as the official views of the Magyar Nemzeti Bank.

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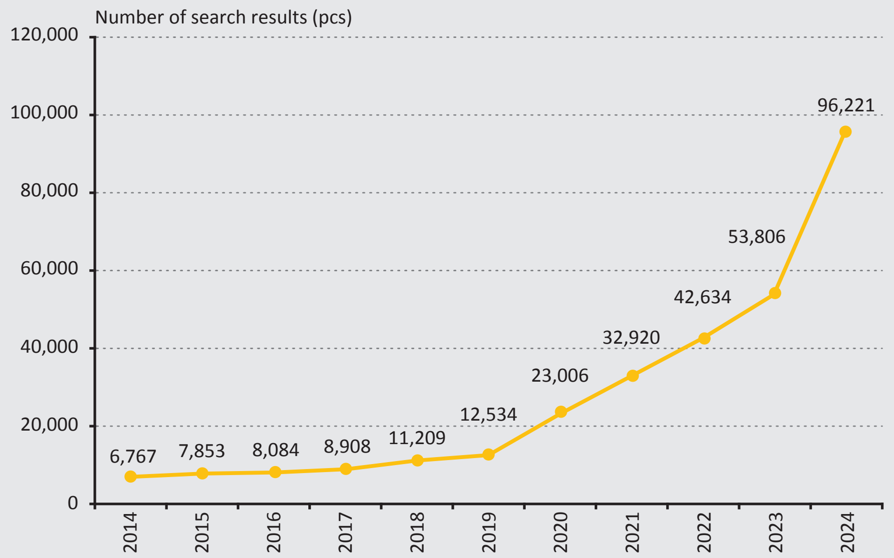
This study is a systematic literature review (SLR) that examines the state of the literature on applications of artificial intelligence in the banking sector. The aim of the research is not to collect new empirical data, but rather to map the international literature according to the PRISMA methodology and to analyse it from the point of view of content, technology and citation. In our research, we systematically review which AI technologies are applied in the financial sector, in which target areas and within which methodological framework, with a special focus on bank failure prediction, risk management and customer relationship development. The aim of the study is to provide a structured summary of the scientific results and to identify the most relevant research trends, thus contributing to the systematic organisation and comparability of the financial AI applications.

Scientific interest and research activity in artificial intelligence has grown significantly over the last decade. *Figure 1* shows that the number of search results for keywords such as "Artificial intelligence" + "finance industry", "Artificial intelligence" + "banking sector", "Artificial intelligence" + "credit scoring", "Machine learning" + "finance", and "Machine learning" + "transaction" is steadily increasing. The figure is based on search results from Google Scholar, Web of Science (WoS) and Scopus, reflecting the state of scientific literature on AI and its applications in the banking sector in the period between 2014 and 2024.

Figure 1
Search trends for artificial intelligence in the financial and banking sector (2014–2024)



Source: Edited based on Google Scholar, Web of Science and Scopus

In the period between 2014 and 2019, the figure shows a moderate increase in interest in AI and its financial applications, with a few thousand hits per year. The first significant jump is seen in 2020, when the number of hits exceeded 23,000. Thereafter, further growth is shown, probably linked to the wider adoption of AI-based financial models and increased digitalisation in banking. Search results increased steadily between 2021 and 2023, before a dramatic jump in 2024. The number of hits in 2024 nearly doubled, compared to the previous year, to more than 96,000. This suggests that AI applications in the banking sector became a real priority in 2023–2024. It is important to note that there is typically a 1–2-year lag (publication delay) between the spread of practical applications of AI and the number of scientific publications on the topic, and thus the search data reflect the scientific coverage of earlier waves of innovation.

Based on search data, the study of the relationship between AI and the financial sector is currently steadily growing. Banks and financial institutions are increasingly using AI-based models for loan approvals, anti-money laundering and personalised financial advice. Trends show that AI is not only emerging as a supplementary technology in the banking systems, but is also becoming a key strategic tool, significantly transforming the way the sector operates and its competitiveness.

Several international studies have examined the applications of AI in banking, with a particular focus on improving customer relationships, risk management and forecasting models. Based on the literature presented in detail in *Section 3*, we can say that these studies have typically focused on a specific sub-area and used different methodological approaches. By contrast, the aim of our study is to provide a comprehensive, systematic analysis that categorises the banking applications of AI thematically and assesses their scientific weight, based on quantitative indicators (citation rate, technology-based distribution). We used the PRISMA methodology to ensure the transparency and reliability of our scientific research. The novelty of the study lies in the combination of a methodology applied to such a wide range of articles with high scientific impact metrics and a multidimensional analytical framework.

In our research, we seek answers to the following research questions and hypotheses, among others:

[Q*1*]: Which artificial intelligence models dominate bank failure prediction and risk management, and why are they the most effective?

[*H1*]: Unsupervised Learning-based solutions dominate in bank failure prediction and risk management, as these models can efficiently identify ambiguous financial patterns and anomalies.

[Q*2*]: How does AI contribute to improving customer relationships?

[*H2*]: Customer relationship optimisation relies primarily on Natural Language Processing and Deep Learning techniques, as these methods can efficiently analyse customer preferences and automate interactions.

[Q*3*]: Which artificial intelligence models are most helpful in improving bank performance and operational efficiency?

[*H3*]: Semi Supervised Learning and Deep Learning techniques play a key role in improving bank performance and efficiency, by helping to automate and optimise the operational processes.

2. Research trends and applications of artificial intelligence in the banking sector – a review of the literature

The rise of artificial intelligence in banking services presents many opportunities and challenges. For customers and financial institutions alike, adoption analysis is key, as the effective integration of AI-based systems can increase operational efficiency and user satisfaction.

The following studies examine *AI Adoption* from various approaches, highlighting the role of technological, psychological and organisational factors.

Research in the field of *Natural Language Processing* has shown that cognitive and emotional factors have a significant impact on AI adoption. Examining the relationship between customer experience and risk attitudes, *Cintamür* (*2024*) found that social influence and emotional motivations encourage adoption, while technology-related anxiety and risk aversion hinder adoption. In relation to mobile banking, *Lee and Chen* (*2022*) showed that intelligence and human characteristics can enhance trust, but can also increase perceived costs.

The application of *Machine Learning* in banking processes is the focus of several studies. *Ikhsan et al.* (*2025)* confirmed in the Indonesian banking sector that AI adoption is driven by perceived ease of use and usefulness, while perceived risk is a barrier. Examining bank managers' knowledge of AI, *Mogaji and Nguyen* (*2021*) highlighted that the regulatory environment and organisational coordination play a key role in AI integration. *Mostafa* (*2009*) has shown that in Arab banks the acceptance of AI-based systems is related to the accuracy of performance evaluation. The more reliable an AI system's evaluation is, the greater the internal organisation's trust in it. A study by *Khaled Alarfaj and Shahzadi* (*2025*), using Deep Learning methods, demonstrated that technological efficiency – in this case, bank fraud detection – also contributes to the adoption of AI, by increasing the financial institutions' sense of security and systemic trust in new technologies.

In the field of *Cognitive Computing*, *Norzelan et al.* (*2024*) analysed the adoption of AI by managers in finance and accounting departments, with a particular focus on the shared services sector. Their results show that perceived usefulness and technical skills are the most important determinants of adoption, while social pressure and a supportive environment are less important.

Taken together, these studies highlight that the adoption of AI in the banking sector is a complex process, shaped by technological characteristics, customer experience and organisational structure. On the consumer side, trust, ease of use and social norms are key, while for the financial institutions, integration challenges and regulatory requirements are the main obstacles.

Improving banking performance and operational efficiency is a key objective for the financial sector, supported by the increasingly effective use of AI. The various methods of *Machine Learning* offer the potential to optimise business models, reduce operating expenses and increase profitability, as the following studies demonstrate. *Bolívar et al.* (*2023*), *González-González et al.* (*2022*) and *Bonaparte* (*2024*) showed that AI-based analytics improve the efficiency of bank business models and increase profitability. Similarly, *Chishti et al.* (*2024*) concluded that a combination of AI and green finance can stabilise business cycles in the long run, reducing financial volatility. In line with this, *Fraisse and Laporte* (*2022*) used Deep Learning models to achieve more accurate capital adequacy forecasts, which can contribute to reducing the banks' regulatory capital requirements. Similar results were obtained by *González-Carrasco et al.* (*2019*), who improved data integration and the accuracy of business decision-making by automating the identification of correlations between banking transactions. *López Lázaro et al.* (*2018*) also demonstrated the efficiency-enhancing role of AI when applied to optimise cash logistics, achieving a 14-per cent cost reduction. In line with this, *Met et al.* (*2023*) found that Auto Machine Learning-based predictions improve the performance evaluation and goal-setting of bank branches. Finally, *Moffo* (*2024*) used Machine Learning models in the field of bank stress testing to achieve more accurate forecasts, which can help design more efficient capital adequacy strategies. The above research clearly demonstrates that the widespread adoption of Machine Learning can lead to significant efficiency gains in all areas of the banking operations, supporting long-term competitiveness.

The further *development of strategic decision-making* is also increasingly relying on artificial intelligence to support financial analysis, forecasting and business strategy development. The following research papers all rely on *Machine Learning* to improve decision-making.

Lu et al. (*2024*) pointed out that AI-based models provide more accurate predictions for analysing the effects of changes in the financial structure than traditional economic models. Similarly, *Ma et al.* (*2025*) showed that sustainable finance has a more significant influence on the fintech market than on AI shares, a key factor in financial strategic decision-making. *Qian et al.* (*2024*) investigated how political uncertainty affects bank lending and the companies' investment decisions, and used Machine Learning models to identify the key influencing factors. Consistent with these, *Tang and Li* (*2023*) demonstrated the accuracy of Deep Learning models in prediction tasks that can help business decision-makers. *Xie et al.* (*2023*) investigated the interpretability of Machine Learning models in bank telemarketing, showing that these tools can help to reach target audiences more accurately and increase the effectiveness of campaigns. *Klein and Walther* (*2024*) investigated financial applications that improve the transparency of AI models in risk management, lending decisions and regulatory compliance.

Natural Language Processing also plays a key role in supporting strategic financial decisions, in particular by analysing textual data. *Katsafados et al.* (*2024*) used Machine Learning-based text analysis to predict bank mergers, showing that the language used by corporate executives can be a reliable indicator of merger intentions. *Sun et al. (2024*) investigated the impact of regulatory changes in the Chinese shadow banking system, using Natural Language Processing and text analysis, which they found to significantly affect bank lending strategies. These studies have shown that Natural Language Processing is an effective tool to support banking regulation and market decision-making.

Artificial intelligence is also playing an increasingly important role in *predicting bank failures*, which is crucial for financial stability. The following studies have all used *Machine Learning* methods to estimate the probability of bankruptcy more accurately. *Gogas et al.* (*2018*) developed a model using Support Vector Machines that separated solvent and failing banks with 99.22-per cent accuracy, outperforming traditional statistical methods. Similarly, *Hu et al.* (*2025*) applied the Random Forest algorithm to predict the failure of US banks, highlighting the importance of capital adequacy ratios for prediction accuracy.

Lagasio et al. (*2022*) were the first to use Graph Neural Networks to investigate the failure risk of euro area banks, showing that market competition affects the probability of failure. In line with this, *Le and Viviani* (*2018*) demonstrated that Artificial Neural Networks provide more accurate bankruptcy predictions than logistic regression, thus helping regulatory decision-making. *Petropoulos et al.* (*2020*) confirmed the effectiveness of the Random Forest method, which showed reliable performance in estimating the probability of failure for both US and European banks. *Asmar and Tuqan* (*2024*) and *Durongkadej et al.* (*2024*) demonstrated that Machine Learning models are effective in identifying threats to digital banks and significantly reduce the risk of failure. These results clearly show that the use of Machine Learning significantly increases the accuracy of bank failure prediction, contributing to the stability of the financial system.

AI is playing an increasingly important role in the *management of banking risks*, enabling more accurate forecasting and better decision-making. The following research papers are based on *Machine Learning* models. *Alonso-Robisco and Carbó* (*2022*) and *Hussein Sayed et al.* (*2024*) found that Machine Learning models provide more accurate predictions, thereby reducing regulatory capital requirements. *Kruppa et al.* (*2013*) and *Lin et al.* (*2025*) demonstrated the benefits of Machine Learning models in predicting consumer and car loan risks using the Random Forest and XGBoost methods. *Mercadier et al.* (*2025*) and *Heß and Damásio* (*2025*) developed a new AI-based approach to identify the global banking system risks, while *Wang et al.* (*2024*) and *Uddin et al.* (*2023*) did the same from the perspective of the impact of banking digitalisation. *Shahbazi and Byun* (*2022*) also developed a similar solution, but for reducing risks in the cryptocurrency markets. *Sugozu et al.* (*2025*) analysed the credit risk of the Turkish banking system and showed that Islamic banks have higher risk exposure, especially in competitive situations, while *Zhou et al.* (*2019*) presented an IoT-based (Internet of Things) financial risk management system that enables faster and more accurate forecasts through parallel calculations.

The only study using *Natural Language Processing* is the work of *Thi Nguyen et al.* (*2024*), which examined the risk analysis of bank capital adequacy ratios and stress tests.

Artificial intelligence is playing an increasingly important role in the *development of banking customer relationships*, supporting the personalisation of offers, and increasing customer satisfaction and the efficiency of financial advice. The use of *Machine Learning* allows for more accurate modelling and prediction of customer preferences. *Bockel-Rickermann et al.* (*2025*) investigated the use of Causal Machine Learning in the optimisation of mortgage loan offers, while *Singh et al.* (*2024*) studied prediction models developed for predicting customer loss, highlighting the effectiveness of the XGBoost and Random Forest methods. Similarly, *Omoge et al.* (*2022*) demonstrated that AI-based Customer Relationship Management (CRM) systems increase customer satisfaction and loyalty, although technological outages may limit their effectiveness. *Northey et al.* (*2022*) showed in their research that consumers trust human advisors more than AI-based robo-advisors, especially for major investment decisions. Deep Learning models are also prominent in predicting customer satisfaction, with *Zeinalizadeh et al.* (*2015*) using neural networks to investigate the main determinants of customer satisfaction.

Natural Language Processing also plays a key role in analysing customer opinions and improving the automated customer service system. *Hentzen et al.* (*2021*) investigated the impact of Natural Language Processing-based Content Extraction on customer engagement, while *Königstorfer and Thalmann* (*2020*) used Sentiment Analysis to analyse customer experiences of AI-based services. The results show that Natural Language Processing is effective in understanding bank interactions, thereby improving the customer experience and optimising marketing strategies.

Our analysis was based exclusively on international academic publications in Q1 journals, with the aim of providing a comprehensive picture of the latest trends in the application of artificial intelligence in finance. Hungarian studies were not included in our analysis, as we wanted to provide an internationally oriented, scientifically authoritative literature review.

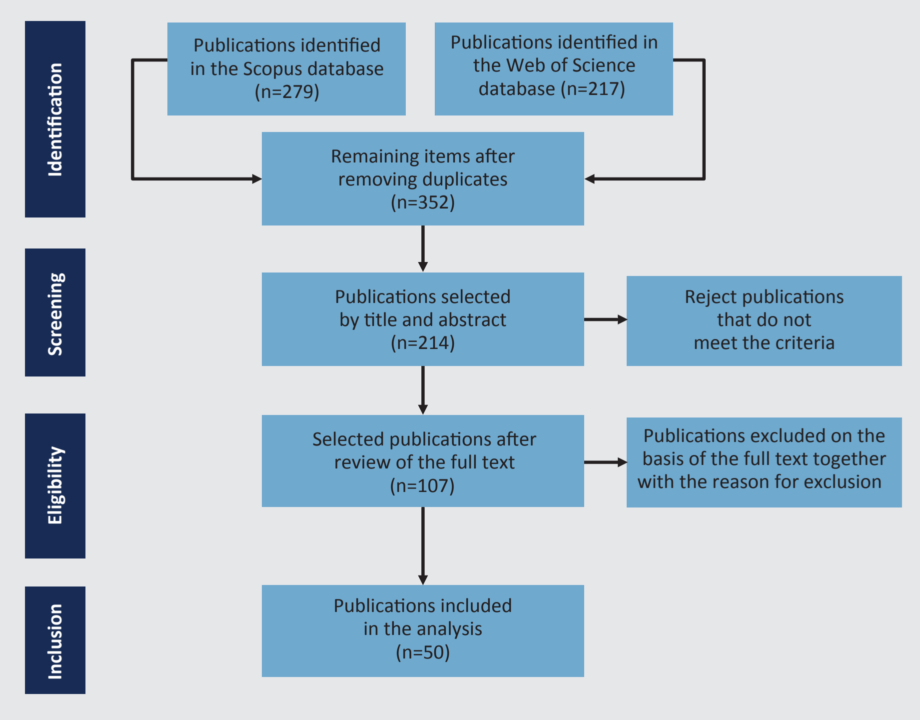
At the same time, it is important to stress that there is growing interest among Hungarian researchers in the application of AI in the financial sector. *Domokos and Sajtos* (*2024*) looked at the key areas of AI use in banking, such as risk management and customer relationship automation, highlighting regulatory issues. *Rajka and Pollák* (*2024*) analysed the application of the XGBoost algorithm in credit risk modelling, showing its predictive advantages. *Bagó* (*2023*) examined the role of Machine Learning and Big Data in banking digitisation. *Prisznyák* (*2022*) gave a detailed presentation on AI-enabled customer service solutions and banking *robotisation*. *Harkácsi and Szegfű* (*2021*) described the relationship between compliance assurance and AI. *Boncz and Szabó* (*2022*) and *Zsinkó* (*2025*) analysed the impact of artificial intelligence on the labour market, while *Benedek and Nagy* (*2023*) showed that AI-based methods for identifying motor insurance fraud are currently less cost-effective than traditional statistical-econometric tools. These studies clearly show that the Hungarian academic discourse is also actively dealing with the financial aspects of AI, which further strengthens the relevance and the niche character of our research, as we go beyond focused case studies and systematically review the whole range of international AI applications in the banking sector.

3. Research methodology

Our research looked at the role of AI in the banking sector, with a particular focus on the types of solutions most commonly used. To this end, we conducted a systematic literature search, collecting the relevant scientific publications from the Scopus and WoS databases.

We used the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (*PRISMA*) *methodology* for our research, which ensures the transparency and reproducibility of the literature review. The analysis consisted of four main steps: *identification, screening, compliance and inclusion.* The process is shown in *Figure 2.*

Figure 2
Mapping of the relevant publications using the PRISMA method



In the identification phase, we applied a predefined search strategy using keywords such as *"Artificial Intelligence"*, *"Machine Learning"*, *"Finance"*, *"Banking"*, *"Credit Scoring"* and similar keywords. As a result, 279 relevant publications were identified in Scopus and 217 in the Web of Science database, and thus a total of 496 studies were included in our initial analysis.

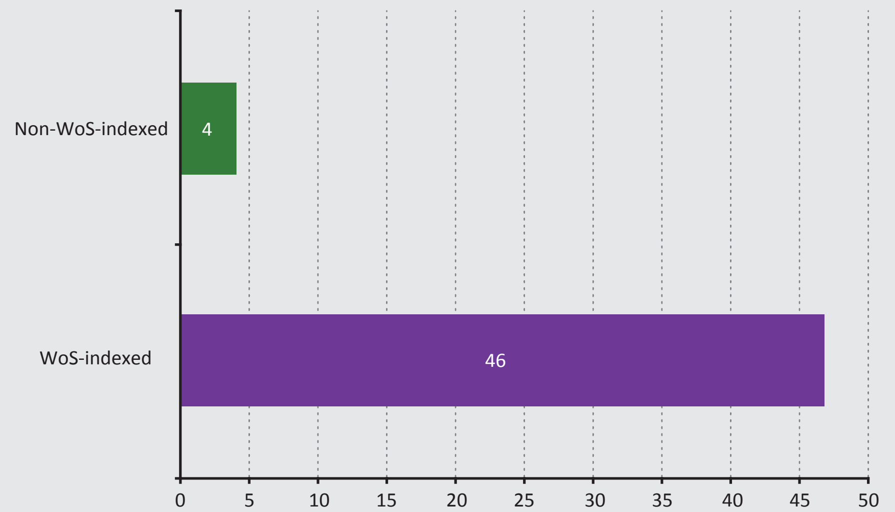
The first step in the *screening phase* was to remove duplicate studies, leaving 352 individual publications. This was followed by a review of the titles and abstracts, to exclude studies that were not closely related to the study of the financial applications of AI. As a result of this step, 214 publications remained in the analysis, while 138 were excluded because they did not meet the analysis criteria.

In the *compliance phase*, we carried out a further screening, which involved the analysis of the full text of the publications. During this process, we assessed the research questions, methodology, databases and relevance of the publications. As a result of the analysis, we finally retained 107 publications and excluded 31 studies, because they did not contain sufficient empirical data or did not directly address the specific cases of AI use.

The final screening in the *inclusion phase* was to identify the most relevant and highest quality studies. To do this, we took into account the impact factor, citation rates and the scientific importance of the publications. Finally, 50 studies were selected for detailed analysis and were categorised thematically according to the different financial applications of AI.

Figure 3 shows the distribution of the selected publications by WoS indexation. Of the 50 studies examined, 46 are included in the WoS database, while 4 are not WoS-indexed. This means that 92 per cent of the studies in the sample come from WoS-indexed sources, while the share of non-WoS-indexed publications is only 8 per cent.

Figure 3
Distribution of the publications by WoS indexation



	WoS-indexed	Non-WoS-indexed
Item number	46	4
Percentage distribution	92%	8%

The high WoS indexation indicates that the majority of the studies included in the analysis were published in peer-reviewed journals, which ensures the reliability and scientific credibility of our literature review. The low ratio of non-WoS-indexed publications indicates that the research relies primarily on internationally recognised sources, minimising the influence of potentially less well-established or lower quality studies on the results.

Table 1 provides the definitions of the artificial intelligence methods used in the research, with their Hungarian and English forms, to facilitate a clear understanding and consistent use of each technique in the study.

Table 1
Artificial intelligence methods and their definitions

AI method	Brief description of the method
Cognitive Computing	AI systems that provide data processing capabilities that mimic human thinking, such as Natural Language Processing, and help solve complex problems via decision support and pattern recognition.
Content Extraction	A Natural Language Processing technique that extracts relevant information from unstructured textual data, such as key indicators from financial reports or relevant legal terms from contracts.
Deep Learning	A specialised branch of Machine Learning that uses Deep Neural Networks to analyse large amounts of data and recognise complex patterns, for example in image recognition, speech recognition and financial forecasting.
Dimensionality Reduction	A Machine Learning technique that reduces the number of variables while retaining the essential characteristics of the data, for example in financial models or customer grouping, to increase the efficiency of data analysis.
Information Retrieval	A Natural Language Processing technique that can extract relevant documents, data or key information from large data sets, for example to search financial reports, legal texts or customer archives.
Machine Learning	An AI method that can learn from data samples and make predictions without the need for explicit programming, for example in credit risk analysis or customer behaviour prediction.
Natural Language Processing	An AI technology that enables computers to interpret, process and generate human language, for example in chatbots, financial report analysis or sentiment analysis of customer reviews.
Question Answering	A Natural Language Processing technique that enables AI to provide accurate and relevant answers to human questions based on structured or unstructured data, for example in customer service chatbots or financial report analysis.
Reinforcement Learning	A Machine Learning method in which an algorithm optimises its decisions based on experimentation and feedback, using a reward system, for example in algorithmic trading or robotics applications.
Semi Supervised Learning	A Machine Learning method that learns by combining small amounts of labelled data with large amounts of unlabelled data, for example in fraud detection or credit risk analysis, where fully labelled data sets are not always available.
Sentiment Analysis	A Natural Language Processing technique that analyses and classifies the emotional content of textual data into positive, negative or neutral categories, for example to assess the emotional sentiment of customer reviews, market news or financial reports.
Text Generation	A Natural Language Processing technique capable of automatically generating human-language text, such as summarising financial reports, generating chatbot responses or producing marketing content.
Topic Modelling	A Natural Language Processing technique used to automatically detect major themes and patterns in large text data sets, for example to categorise financial reports, customer reviews or market analysis.
Unsupervised Learning	A Machine Learning method that searches for patterns and structures in unlabelled data, for example in customer segmentation or anomaly detection in the financial sector.

Source: Based on Khosravi et al. (2023)

4. Quantitative analysis of the application of artificial intelligence techniques

Table 2 shows the quality, distribution and relevance of the sources of the literature reviewed, which indicates that the research is based on a solid scientific foundation. All sources are from Q1 journals that ensure a high level of peer review and recognised research results.

Table 2
Rating of the sources of the literature reviewed and citations

Journal	Rating	H-index	Number of citations
Borsa Istanbul Review	Q1	42	1
Computers and Industrial Engineering	Q1	161	1
Data Science and Management	Q1	13	1
Decision Support Systems	Q1	180	1
Digital Business	Q1	13	1
Ecological Informatics	Q1	77	1
Engineering Applications of Artificial Intelligence	Q1	137	1
European Journal of Operational Research	Q1	305	2
Expert Systems with Applications	Q1	271	3
Finance Research Letters	Q1	101	4
Heliyon	Q1	88	1
IEEE Access	Q1	242	6
Information Sciences	Q1	227	2
International Journal of Bank Marketing	Q1	104	7
International Journal of Cognitive Computing in Engineering	Q1	16	1
International Journal of Forecasting	Q1	119	2
International Journal of Information Management Data Insights	Q1	34	1
International Review of Economics & Finance	Q1	78	1
International Review of Financial analysis	Q1	91	3
Journal of Banking & Finance	Q1	197	1
Journal of Behavioural and Experimental Finance	Q1	39	1
Journal of Financial Stability	Q1	73	1
Pacific-Basin Finance Journal	Q1	75	3
Research in International Business and Finance	Q1	73	2
Technological Forecasting and Social Change	Q1	179	2

Among the journals surveyed, there are several journals with high H-index scores, such as the European Journal of Operational Research (H-index: 305), Expert Systems with Applications (H-index: 271) and IEEE Access (H-index: 242). These journals are leaders in the fields of artificial intelligence, data processing and decision support. Journals focusing on the financial and banking sector, such as the Journal of Banking & Finance (H-index: 197) and Finance Research Letters (H-index: 101) are also publishing platforms with a significant impact.

Based on the thematic distribution of the resources, the analysis of financial applications of AI reflects a multidisciplinary approach. In particular, journals such as the International Journal of Bank Marketing (7 articles), IEEE Access (6 articles) and Finance Research Letters (4 articles) frequently discuss the relationship between AI and the banking sector. The use of data analysis and Machine Learning is supported by publications in the Expert Systems with Applications and the Engineering Applications of Artificial Intelligence journals. The International Journal of Forecasting and the Journal of Financial Stability play a prominent role in financial stability and forecasting.

Overall, the literature reviewed covers a wide range of disciplines, including AI-based decision making, banking risk analysis, customer relationship management and economic forecasting. This ensures that our study provides a comprehensive assessment of the artificial intelligence trends in the financial and banking sector.

Research on AI applications in finance and banking has accelerated significantly in recent years, as shown by the distribution of citations by year (*Table 3*).

Table 3
Distribution of cited studies by year

Year	Number of cited studies
2009	1
2013	1
2015	1
2018	3
2019	2
2020	2
2021	2
2022	8
2023	5
2024	16
2025, until March	9

Between 2009 and 2021, interest in the area showed a gradual but moderate increase, with the first significant jump in 2018. Publication activity increased from 2022 onwards, reaching a peak in 2024 (16 citations), matching the dramatic surge in search hits during this period. This trend suggests that AI in the banking sector will become a truly central research topic, with recent studies increasingly shaping the technological evolution of the sector. The increasing use of AI-based models by banks and financial institutions for credit assessment, anti-money laundering and customer relationship development indicates that AI is becoming a key strategic factor in the financial sector, rather than just a support tool.

Table 4 presents the different applications of AI in the banking sector, based on the distribution of AI categories and subcategories, as well as on the citation data. In the quantitative analysis of the application of AI in the banking sector, literature searches were conducted using English keywords, and thus in order to present the results consistently and accurately, the AI categories and methods are also presented in English. This ensures clear terminological consistency and allows the comparison of the results with international research.

The field of AI adoption is dominated by Machine Learning and Natural Language Processing techniques, with Semi Supervised Learning (372 citations) and Unsupervised Learning (191 citations) playing a prominent role. Deep Learning and Question Answering systems are less cited areas, but remain important in the study of AI adoption.

Improving bank performance and operational efficiency is mainly based on Unsupervised Learning models (85 citations, 5 references), while Deep Learning (37 citations) and Dimensionality Reduction (5 citations) are also significant. Text Generation models play a smaller but relevant role (11 citations, 2 references).

Unsupervised Learning models dominate in the field of bank failure prediction (502 citations, 4 references), indicating their importance in predicting financial stability. Supervised Learning and Deep Learning received fewer citations (20 for Supervised Learning, 0 for Deep Learning), but remain relevant areas.

In risk management, Unsupervised Learning (317 citations) and Deep Learning (126 citations) are of paramount importance, as they provide accurate predictions. Reinforcement Learning (51 citations) plays a role in risk modelling, while Information Retrieval solutions are less prominent (3 citations, 1 reference).

The development of strategic decision-making is mainly supported by Unsupervised Learning (11 and 3 citations, respectively, in several references), while Deep Learning (6 citations) and Dimensionality Reduction (2 citations) are also mentioned. Topic Modelling techniques show low citation rates (0 citations).

Table 4
Distribution of AI applications in the banking sector

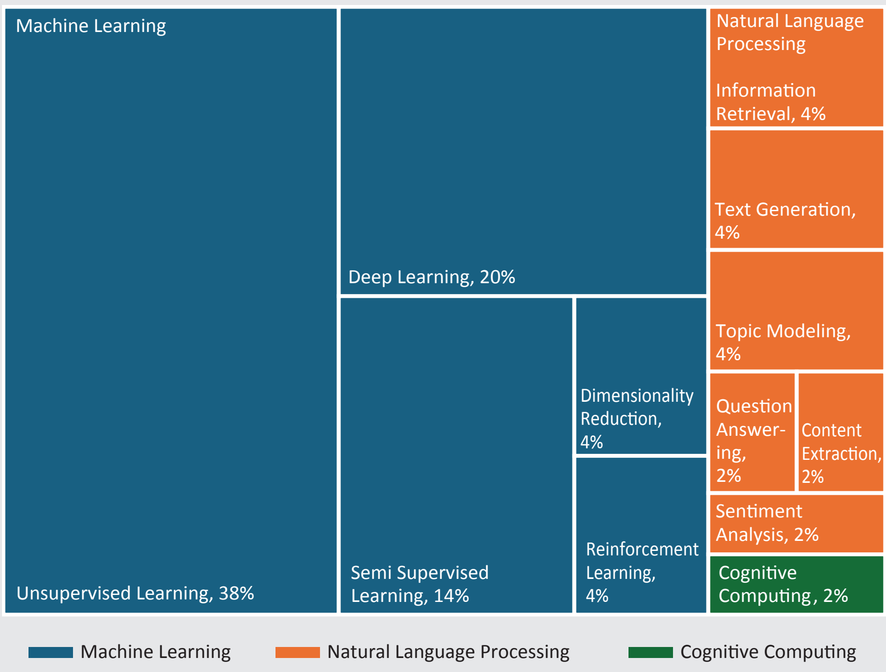
Area	AI category	AI subcategory	Citations	Number of cited studies
AI adoption	Cognitive Computing	–	45	1
	Machine Learning	Deep Learning	0	1
		Semi Supervised Learning	372	2
		Unsupervised Learning	191	1
	Natural Language Processing	Question Answering	7	1
		Topic Modelling	168	1
Improving bank performance and operational efficiency	Machine Learning	Deep Learning	37	1
		Dimensionality Reduction	5	1
		Semi Supervised Learning	63	1
		Unsupervised Learning	85	5
	Natural Language Processing	Text Generation	11	2
Bank failure prediction	Machine Learning	Deep Learning	20	2
		Semi Supervised Learning	0	1
		Unsupervised Learning	502	4
Risk management	Machine Learning	Deep Learning	126	3
		Reinforcement Learning	51	1
		Semi Supervised Learning	71	2
		Unsupervised Learning	317	4
	Natural Language Processing	Information Retrieval	3	1
Developing strategic decision-making	Machine Learning	Unsupervised Learning	11	1
		Deep Learning	6	1
		Dimensionality Reduction	2	1
		Unsupervised Learning	3	3
	Natural Language Processing	Information Retrieval	20	1
		Topic Modelling	0	1
Developing customer relationships	Machine Learning	Deep Learning	151	2
		Reinforcement Learning	74	1
		Semi Supervised Learning	40	1
		Unsupervised Learning	0	1
	Natural Language Processing	Content Extraction	193	1
		Sentiment Analysis	314	1

Both Natural Language Processing and Machine Learning are key to improving customer relationships. Sentiment Analysis is highly cited (314 citations), while Deep Learning models (151 citations) also play a significant role. Content Extraction (193 citations) and Reinforcement Learning (74 citations) help automate and personalise customer relations.

The results are consistent with the growing role of AI applications in the financial and banking sector, where Unsupervised Learning, Deep Learning and Sentiment Analysis are of paramount importance in business applications.

Figure 4 shows the distribution of the different categories and subcategories of AI, based on the articles studied.

Figure 4
Distribution of the categories and subcategories of artificial intelligence



The most dominant method is Unsupervised Learning (38%), which is particularly important in bank failure prediction and risk management, where the analysis of large, unstructured data and the recognition of patterns are needed. The widespread use of Unsupervised Learning shows that this approach is the most common in predicting financial instability and managing credit risks.

This is followed by Deep Learning (20%), which is mainly used to improve customer relationships and increase banking efficiency, in particular in the optimisation of automated customer service systems and personalised financial offers. Semi Supervised Learning (14%) also has a significant role to play, mainly in testing the adoption of AI and improving bank performance, as it combines the benefits of Supervised and Unsupervised Learning, thus leading to more efficient decision support systems.

Of the Natural Language Processing techniques, the use of Information Retrieval (4%) stands out, which plays a significant role in supporting customer relationships and risk management. Topic Modelling (4%) and Text Generation (4%) are also important areas, especially in the analysis and automated reporting of bank text data. Although less prevalent, Sentiment Analysis (2%) and Content Extraction (2%) also contribute to customer experience analysis.

Reinforcement Learning (4%) is mainly used to improve financial advice and customer interaction systems, enabling optimised decision-making in a dynamic financial environment.

This analysis confirms that different forms of AI are used for different purposes in the banking sector. While Unsupervised Learning dominates in bankruptcy and risk prediction, Natural Language Processing methods are mostly used to optimise customer relationships and marketing. Deep Learning is mainly used in efficiency-enhancing applications such as automated customer service and financial advice, while Reinforcement Learning and Semi Supervised Learning contribute to the development of dynamic financial models.

5. Discussion

Our research can be characterised as unique in three ways:

1. by rigorously applying the PRISMA methodology, we provide a structured literature review of AI technologies in the banking sector, which has not been covered in such detail in previous studies;

2. the literature reviewed is quantitatively classified according to the main categories and subcategories of AI, and thus the novelty of the study is the combination of bibliometric analysis and trend-based AI classification;

3. we present impact factors based on citation data using tables and graphs, to draw specific conclusions on future research and application opportunities. All of these factors combined result in the practical usefulness and scientific relevance of our research.

In the following, we compare the results of the relevant studies with our own research, highlighting the key parallels and differences in the application of AI in the financial sector. We then analyse our own results in detail, and refer back to the hypotheses formulated in our research, assessing their confirmation or possible modification in light of the empirical data.

Mishra et al. (*2023*) studied the role of AI and machine learning in the banking sector, with a particular focus on risk management, fraud detection and customer relationship optimisation. Similar to our research, their results show that Unsupervised Learning dominates in the area of bankruptcy prediction and risk analysis, while Natural Language Processing and Deep Learning are tools for customer relationships and efficiency improvement. In addition, the study highlighted the financial integration of large language models and blockchain technology, which, in line with the results of our research, shows that different AI technologies serve different purposes within the financial sector.

Almubaydeen et al. (*2025*) investigated the role of AI in improving the quality of accounting information in banking, in particular through the use of expert systems and automatic learning. Their results confirm our research that Unsupervised Learning (38%) and Deep Learning (20%) play a key role in predicting bank failures, managing risk and improving customer relationships.

Furthermore, our research also showed that Natural Language Processing techniques (Sentiment Analysis, Information Retrieval) support the efficiency of data processing and the speed of financial decision-making, which is in line with the authors' findings.

In their study, *Al-Hawamdeh and AlShaer* (*2022*) investigated the impact of AI on banking innovation, highlighting the use of Fuzzy Logic Systems. Our research confirms that AI serves different purposes in different areas.

Unsupervised Learning is dominant in financial risk analysis and bankruptcy prediction, while Natural Language Processing and Deep Learning can be used to improve customer relationships and operational efficiency.

In addition, both studies emphasise the rapid evolution of AI and the need for institutions to continuously adapt to technological changes, which our research supports by examining the different regulatory and innovation challenges of AI.

Taken together, the results of these four studies and our own research show that the application of AI in banking is bringing significant changes in the areas of risk analysis, customer relationships and decision-making. Unsupervised Learning dominates in the areas of bankruptcy modelling and risk analysis, while Natural Language Processing and Deep Learning focus on improving customer service and banking efficiency. Regulatory and ethical issues are central to all of the research papers reviewed, demonstrating that the transparency and compliance of financial AI solutions is key to the further development of the sector.

The results of our research show that AI is playing an increasingly important role in the banking sector, especially in key areas such as bank failure prediction, risk management, customer relationship development and strategic decision support. In the course of the study, the most dominant AI technologies belonged to the categories of Machine Learning and Natural Language Processing, particularly through Unsupervised Learning, Deep Learning, and Sentiment Analysis methods.

The results clearly support hypothesis [*H1*] that Unsupervised Learning-based solutions dominate bank failure prediction and risk management. The citation data show that this method has the highest literature support (502 citations in bank failure prediction and 317 citations in risk management), suggesting that these models are effective in identifying ambiguous financial patterns and anomalies. By contrast, Deep Learning and Semi Supervised Learning are less dominant in this field, suggesting that although these technologies can provide accurate predictions, Unsupervised Learning methods are more effective for independent pattern recognition.

Consistent with hypothesis [*H2*], the results show that the optimisation of customer relationships relies on Natural Language Processing and Deep Learning techniques. Natural Language Processing and Sentiment Analysis solutions showed a very high citation rate (314 citations), indicating that customer communication and market preference analysis are key factors in bank marketing and customer service strategies. The high number of citations for the use of Deep Learning (151 citations) also confirms the growing role of automated customer service systems and personalised offers in the financial sector.

Our research also supports hypothesis [*H3*] that Semi Supervised Learning and Deep Learning techniques play an important role in improving bank performance and operational efficiency. The citation data show that Semi Supervised Learning (63 citations) and Unsupervised Learning (85 citations) methods contribute significantly to operational process optimisation and automated decision-making. These results also confirm that hybrid learning models in the banking sector – combining the benefits of Supervised and Unsupervised Learning – can be particularly effective in automating business processes.

One important finding of our research is that the use of AI in the banking sector has accelerated significantly in recent years, as the distribution of studies cited by year shows.

The number of AI-related publications has risen sharply from 2019 onwards, peaking in 2024, indicating that AI has become a strategic technology in the banking sector. Trends show that financial institutions are increasingly relying on Machine Learning and Natural Language Processing to optimise business decision-making, risk management and customer relationships.

The results of the research highlight that the deepening integration of AI into the banking sector's operations not only helps to increase efficiency and optimise risk management, but also provides a long-term strategic advantage for the financial institutions.

The dominance of Unsupervised Learning in predicting bankruptcy and risk analysis, and the key role of Natural Language Processing and Deep Learning in improving customer relationships, suggest that AI applications are becoming more targeted and increasingly sophisticated.

Improving the interpretability and transparency of AI, especially for Unsupervised Learning models where decision-making processes are difficult to reverse engineer, could be a priority for future research. In addition, the dynamic evolution of the regulatory environment warrants further research on the ethical and legal issues of AI, in particular in the areas of automated decision-making and the personalisation of financial services.

Expected trends in technological development include the increased integration of large language models and generative AI systems in the financial sector, which could open up new opportunities for automating customer services and data-driven decision-making. The combined use of AI and blockchain technology is also a promising area that can contribute to increasing the security and transparency of financial transactions.

Ultimately, the development of artificial intelligence will not only transform current financial processes, but will also become a key factor in the future competitiveness of the banking sector. Accordingly, future research should pay more attention not only to technological innovations, but also to the risks and regulatory challenges they entail.

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