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The Evolution of Machine Learning in Banking: A Bibliometric Mapping and Systematic Literature Review

Ayu Danavia[1], Anggi Aprizal[2]
[1,2]Akademi Bisnis Lombok. Lombok Utara, Indonesia
Corresponding Author : danavia01@gmail.com

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Abstract

The rapid adoption of artificial intelligence (AI) and machine learning (ML) has transformed the banking sector, particularly in risk management, predictive analytics, fraud detection, customer behavior analysis, and financial decision-making. However, research on ML in banking remains fragmented across methodological and application domains, while emerging issues such as cybersecurity, privacy, explainability, ethical AI, and financial resilience receive comparatively less attention. This study aims to systematically map and analyze the evolution of ML research in banking by identifying dominant methodologies, research themes, conceptual relationships, temporal developments, and emerging research gaps. The study employs a Systematic Literature Review (SLR), bibliometric mapping, and content analysis based on 53 curated scientific articles. Literature selection follows the PRISMA framework, while bibliometric analysis uses VOSviewer through network, overlay, and density visualizations. The findings identify seven major research clusters: integrated banking predictive analytics; supervised ML for credit risk, fraud, and customer churn; deep learning and hybrid ML–DL; ensemble learning and imbalanced data handling; unsupervised learning and customer segmentation; anomaly detection and cybersecurity; and privacy-preserving, federated learning, and ethical AI. The results indicate that ML remains the dominant research theme, with deep learning, artificial neural networks, risk assessment, accuracy, and efficiency representing highly developed areas. Temporal analysis demonstrates a shift from conventional predictive methods toward deep learning, cybersecurity, privacy, blockchain, and emerging AI technologies. Nevertheless, predictive performance remains dominant, while explainability, privacy, fairness, governance, and financial stability remain comparatively underdeveloped. The study concludes that future banking ML research should move beyond algorithmic accuracy toward integrated frameworks combining predictive analytics with responsible AI, cybersecurity, privacy protection, financial stability, and institutional governance.

Keywords: Risk Management, Financial Technology, Cybersecurity, Ethical AI

Introduction

The banking and financial sector is undergoing profound transformation driven by digitalization, large-scale data availability, and the adoption of artificial intelligence (AI) and machine learning (ML). Financial institutions increasingly use ML to improve operational efficiency, risk management, customer services, and strategic decision-making, particularly in credit scoring, fraud detection, customer churn prediction, financial forecasting, investment analysis, and automated decision support (Warin & Stojkov, 2021; Singh, 2025).

Risk management represents one of the most prominent applications of ML in banking. Banks face credit, market, operational, liquidity, and cybersecurity risks, while the increasing complexity of financial data has encouraged the use of ML techniques capable of identifying nonlinear relationships and hidden patterns beyond conventional statistical models. Although ML can improve the predictive performance and efficiency of credit risk assessment, challenges related to robustness, interpretability, and regulatory compliance remain important (Rodríguez et al., 2024; Machine learning in banking risk management, 2025). Similarly, the expansion of digital banking and online transactions has increased exposure to fraud and cyber threats. ML and deep learning can detect suspicious patterns and anomalies, although highly imbalanced fraud datasets create methodological challenges and encourage the use of ensemble learning, deep learning, and resampling techniques (Al-Hashedi & Magalingam, 2021; El-Yassini et al., 2023).

Beyond risk and fraud detection, ML is increasingly applied to customer analytics and decision-support systems. Supervised learning supports customer churn prediction and financial classification, while unsupervised learning identifies latent patterns and customer segments. Deep learning further enables the processing of sequential and heterogeneous financial data, reflecting a transition toward integrated intelligent systems for risk management, customer analysis, and strategic decision-making (Singh, 2025).

However, the rapid adoption of ML also raises concerns regarding transparency, explainability, fairness, privacy, and regulatory accountability. Complex "black-box" models may make financial decisions difficult to understand, particularly in credit approval, risk classification, and fraud detection. Consequently, Explainable Artificial Intelligence (XAI) has emerged as an important research area for improving transparency, trust, and accountability in financial AI systems (Černevičienė & Kabašinskas, 2024; AlSaleh et al., 2025). Increasing attention is also directed toward privacy preservation, ethical AI, consumer protection, and responsible technology governance, indicating a shift from performance-oriented research toward trustworthy and sustainable AI (Fundira & Mbohwa, 2025; Černevičienė & Kabašinskas, 2024).

Despite the growing literature, research remains fragmented across credit risk, fraud detection, cybersecurity, privacy, and ethical AI. Existing studies also demonstrate increasing methodological diversity, including supervised and unsupervised learning, ensemble methods, deep learning, and hybrid approaches (Bajwa et al., 2023; Rodríguez et al., 2024; Warin & Stojkov, 2021). Therefore, an integrated mapping is needed to understand the intellectual structure, relationships, and evolution of banking and ML research.

This study aims to systematically map the development of banking and ML research using Systematic Literature Review (SLR), bibliometric mapping, and content analysis. Based on 53 curated scientific articles, VOSviewer is employed through network, overlay, and density visualizations. The study identifies major research streams encompassing predictive analytics, credit risk and fraud detection, deep learning and hybrid approaches, ensemble learning, customer segmentation, anomaly detection, cybersecurity, privacy-preserving technologies, federated learning, and ethical AI. By integrating systematic literature selection, bibliometric visualization, and content analysis, this study contributes a structured understanding of dominant methods, conceptual relationships, temporal developments, and emerging research opportunities, particularly in cybersecurity, privacy, explainability, ethical AI, data governance, and financial resilience.

Research Method

This study employs a Systematic Literature Review (SLR) combined with Bibliometric Mapping to analyze the development of research on banking and machine learning. This approach identifies, organizes, and maps research themes, analytical methods, keywords, conceptual relationships, and emerging issues, while providing a systematic overview of the intellectual structure of a research field (Donthu et al., 2021). The study focuses on machine learning applications in banking and finance, particularly credit risk prediction, fraud detection, customer churn, financial stability, customer segmentation, cybersecurity, privacy, and financial decision-support systems.

The SLR ensures systematic literature selection based on relevance, publication quality, and methodological contribution. The final dataset consists of 53 curated scientific articles, which were systematically analyzed and mapped using VOSviewer. To ensure transparency and traceability, the study adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, covering identification, screening, eligibility, and inclusion/exclusion stages (Sahoo, Saraf, & Uchil, 2024). This procedure supports a structured mapping of research developments, dominant themes, and future research opportunities (Wiranatakusuma, Aprizal, & Kamil, 2024).

The literature collection began with the identification of studies related to banking, machine learning, artificial intelligence, financial analytics, credit risk, fraud detection, customer churn, financial decision support, cybersecurity, and financial services. Searches employed combinations of keywords including "banking," "machine learning," "artificial intelligence," "financial risk," "credit risk," "fraud detection," and "customer churn." During screening, studies that were not substantively related to machine learning applications in banking and finance were excluded. The eligibility stage subsequently assessed titles, abstracts, research themes, and methodological relevance, resulting in 53 articles for analysis.
The selected bibliographic data were organized using Microsoft Excel 365 and supported by Publish or Perish, while VOSviewer was employed for bibliometric analysis. Three visualization techniques were applied: network, overlay, and density visualization. Network visualization identifies keyword relationships and cluster structures; overlay visualization examines the temporal evolution of research themes; and density visualization identifies dominant and less-developed topics. The mapping indicates a transition from earlier methodological themes such as artificial neural networks, logistic regression, and nearest neighbors toward deep learning, big data, and deep neural networks, followed by emerging themes such as large language models, blockchain, privacy, malware, and cyber risk.

The bibliometric findings were strengthened through content analysis to provide substantive interpretation of keyword relationships and research clusters (Aprizal et al., 2024). The literature was classified into seven major clusters: (1) Integrated Banking Predictive Analytics; (2) Supervised Machine Learning for Credit Risk, Fraud, and Churn; (3) Deep Learning and Hybrid ML–DL; (4) Ensemble Learning and Imbalanced Data Handling; (5) Unsupervised Learning and Customer Segmentation; (6) Anomaly Detection and Cybersecurity; and (7) Privacy-Preserving, Federated Learning and Ethical AI, complemented by conceptual, qualitative, and review dimensions.

Finally, research gaps were identified by comparing dominant and emerging themes, particularly low-density areas such as blockchain, privacy, cybersecurity, malware, large language models, and data governance (Zultaqawa, Alexandri, & Hardinata, 2019). Content analysis further examined methodological limitations and opportunities for cross-disciplinary integration (Zuhroh, 2022). Overall, the integration of SLR, bibliometric mapping, and content analysis provides a comprehensive basis for identifying research trends and future directions concerning financial risk management, digital banking, cybersecurity, privacy, ethical AI, financial resilience, and data governance.

Result and Discussion

This section presents the main findings of the systematic literature review (SLR) conducted on 53 curated scientific articles that discuss the relationship between the banking sector and the application of machine learning. The main focus of this analysis is directed at two key aspects. First, mapping the most widely used machine learning analysis methods in banking studies. Second, the visualization and development structure of the research theme identified through bibliometric analysis using VOSviewer.
Through the SLR approach, this study ensures that the articles analyzed have gone through a systematic and rigorous selection process, both in terms of topic relevance, publication quality, and methodological contribution. Thus, the results presented not only reflect quantitative trends, but also illustrate the direction of scientific development (state of the art) in banking and machine learning studies.

Method analysis is focused on identifying dominant algorithms and analytical approaches, such as supervised learning, unsupervised learning, ensemble methods, and evaluation techniques commonly used in the banking context—for example, in credit risk prediction, fraud detection, customer churn, and financial stability. The discussion in this section not only highlights the frequency of using the method, but also relates it to the purpose of the research and the complexity of the banking problems being handled.

Furthermore, the results of the VOSviewer analysis were used to map the conceptual structure and relationships between topics in the literature. Network visualization, overlay visualization, and density visualization provide an overview of research clusters, the evolution of themes over time, and the degree of dominance of certain topics in banking and machine learning studies. This approach allows for the identification of established research areas, while also uncovering research spaces that are still open to development.

By combining methodological analysis and bibliometric mapping, this results and discussion section is expected to be able to provide a comprehensive understanding of how machine learning is used in banking studies, as well as how the dynamics and direction of research in this field develop systematically and in a structured manner.

Result of Literature Review Banking and Machine Learning

Integrated Banking Predictive Analytics Cluster (IBPAC)
The integration of diverse machine learning methodologies from recent studies illustrates that predictive systems in the banking sector can be constructed in a more holistic and adaptable fashion. Research conducted by Mena et al., (2024) highlights the significance of employing symbolic classifiers to improve financial risk prediction by tackling class imbalance and preserving a balance between model accuracy and interpretability. In the banking sector, class imbalance frequently arises due to the much lower incidence of defaults or fraud compared to standard transactions, potentially leading to prediction bias if inadequately addressed. Consequently, methodologies like data resampling and cost-sensitive learning are crucial for ensuring reliable and equitable risk assessment. This methodology is especially crucial in banking, where predictive models must attain high accuracy while

simultaneously ensuring transparency and explainability to adhere to financial regulations and governance norms. Additionally, Li et al., (2024) study integrates economic data and market sentiment into bond yield forecasting through the utilization of Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models. RNN is a deep learning model intended for sequential or time-series data processing, whereas LSTM is an enhanced RNN architecture that effectively captures long-term dependencies and mitigates the vanishing gradient problem. In banking applications, these models can be employed to predict interest rates, market risk exposure, asset price volatility, and macroeconomic factors that affect bank stability and profitability. Research by Hanae et al., (2023) presents a machine learning-based architecture for real-time, end-to-end fraud detection in digital security. This technology continuously analyzes transaction data to detect anomalies or suspect patterns in electronic banking activity. This strategy is particularly pertinent in the age of digital transformation, as substantial transaction volumes necessitate predictive systems that are rapid, adaptable, and proficient in reducing false positives while ensuring robust fraud prevention efficacy.
Simultaneously, research conducted by (Aldelemy & Abd-Alhameed, 2023; Bhuria et al., 2025). underscores the efficacy of diverse categorization algorithms in forecasting online purchasing behavior and consumer attrition. The methods encompass Naïve Bayes (a probabilistic classifier derived from Bayes' Theorem), Decision Trees (hierarchical decision models), Random Forest (an ensemble of numerous decision trees), Support Vector Machines (SVM), Logistic Regression, Artificial Neural Networks (ANN), AdaBoost (Adaptive Boosting), and Gradient Boosting. Furthermore, ensemble learning methods like the voting classifier integrate various models to improve predicted consistency and overall efficacy.

The integration these methodologies, a cohesive predictive framework for banking can be delineated into four primary dimensions: (1) credit risk and financial stability forecasting employing interpretable and imbalance-sensitive models; (2) macroeconomic and market predictions utilizing deep learning time-series architectures such as RNN and LSTM; (3) customer behavior and retention analysis through classification and ensemble techniques; and (4) real-time fraud detection within digital banking systems. This cohesive framework constitutes an Integrated Banking Predictive Analytics Framework, a thorough predictive system aimed at improving accuracy, interpretability, risk resilience, and strategic decision-making inside contemporary banking institutions.

Thematic Cluster Analysis of Machine Learning Research in Banking

The bibliometric and content analysis identifies seven major research clusters reflecting the methodological and conceptual development of machine learning (ML) applications in banking and finance. These clusters demonstrate an evolution from conventional predictive analytics toward more adaptive, secure, privacy-preserving, and ethically responsible financial intelligence systems.
First, the Supervised Machine Learning for Credit Risk, Fraud, and Churn cluster represents the mainstream of banking ML research. Studies predominantly formulate loan default, credit card fraud, and customer churn as binary or multiclass classification problems (SharafEldin et al., 2025; Tam-Luong et al., 2025; Rana et al., 2025; Tam et al., 2025). Logistic Regression remains an important baseline because of its interpretability and regulatory suitability, while Decision Tree and Random Forest are used to capture nonlinear relationships and improve predictive performance. Gradient Boosting and ensemble approaches further enhance prediction, particularly for fraud and churn. Feature engineering and selection, including SHAP and mRMR, are also important for improving both performance and interpretability. A recurring methodological challenge is class imbalance, which has encouraged the use of resampling, ensemble learning, F1-score, and AUC. Overall, this cluster confirms supervised ML as a fundamental analytical instrument for credit scoring, fraud monitoring, and customer retention.

Second, the Deep Learning and Hybrid Machine Learning–Deep Learning cluster reflects a methodological transition toward more sophisticated financial decision-support systems. Deep learning models are increasingly applied to sequential, heterogeneous, and high-dimensional financial data. RNN and GRU architectures are used to capture temporal patterns, while CNN and GRU combinations support automated feature extraction and credit decision-making. Autoencoders are employed to identify latent structures in complex financial data, while Transformer architectures provide opportunities for modeling long-term dependencies. Hybrid ML–DL approaches seek to combine the predictive capabilities of deep learning with the interpretability and implementation advantages of conventional ML. Nevertheless, data requirements, computational costs, and model explainability remain important challenges.

Third, the Ensemble Learning and Imbalanced Data Handling cluster emphasizes methodological robustness in situations where critical financial events are relatively rare. Credit default, fraud, and financial distress datasets are typically characterized by severe class imbalance, creating the risk of misleadingly high accuracy. Ensemble methods, including Random Forest, combined with cluster-based undersampling, can improve minority-class detection while preserving relevant information. Synthetic oversampling methods such as SMOTE and CDSMOTE provide additional strategies for increasing minority-class representation. Consequently, evaluation increasingly emphasizes AUC-ROC, G-Mean, recall, F1-score, and expected cost rather than accuracy alone. This cluster highlights that effective financial risk modeling depends not only on algorithm selection but also on appropriate data representation and risk-sensitive evaluation.

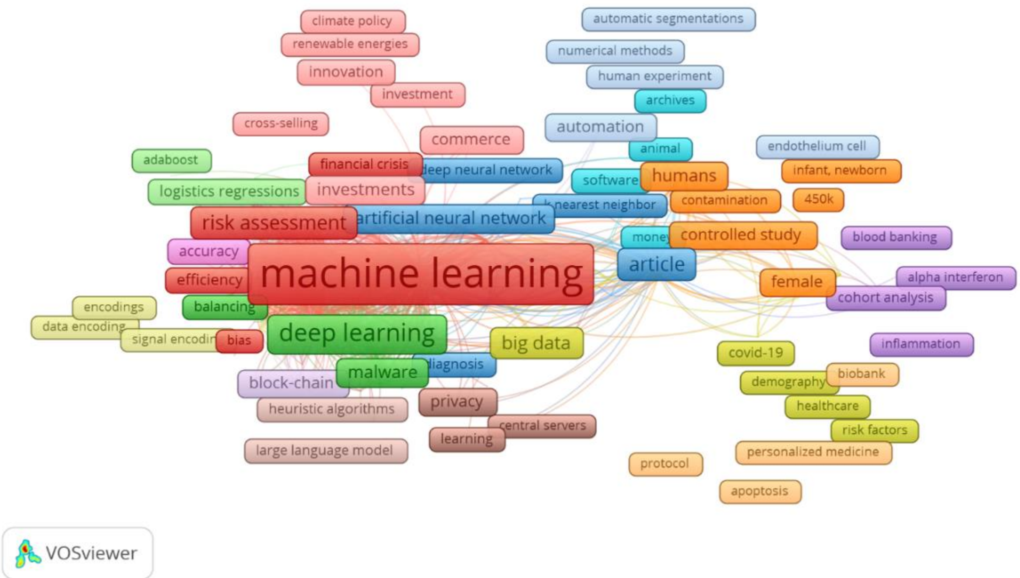
Fourth, the Unsupervised Learning and Customer Segmentation cluster focuses on identifying latent structures without predefined target variables. K-means, hierarchical clustering, distance-based analysis, and spatial clustering are used to identify heterogeneous customer profiles, institutional characteristics, and geographical patterns. This approach supports customer profiling, risk concentration analysis, and financial inclusion strategies. Importantly, unsupervised learning can serve as a methodological bridge between exploratory analysis and supervised prediction by generating contextual segments that can subsequently inform risk classification and decision-making.

Fifth, the Anomaly Detection and Cybersecurity in Banking cluster expands ML applications from conventional financial risks toward digital and systemic security threats. The increasing use of mobile banking, cloud systems, APIs, and interconnected platforms has intensified cybersecurity risks. Unsupervised anomaly detection is particularly relevant where attack labels are unavailable, enabling systems to identify deviations from normal behavioral patterns. Hybrid supervised–unsupervised approaches further strengthen the detection of both known and emerging threats, while biometric ML provides additional layers of behavioral authentication. Thus, ML increasingly functions as part of banking cyber-resilience infrastructure rather than merely as an analytical tool.

Sixth, the Privacy-Preserving, Federated Learning, and Ethical AI cluster represents a shift from performance-centric toward trust-centric ML. Federated learning enables models to be trained across distributed institutions without transferring raw financial data, thereby supporting collaborative analytics while preserving privacy. Privacy-preserving optimization and knowledge distillation further address sensitive-data protection. At the same time, fairness, explainability, auditability, data governance, and regulatory accountability have become increasingly important. This cluster demonstrates that AI adoption in banking must balance predictive performance with consumer protection, ethical responsibility, and institutional trust.

Seventh, the Conceptual, Qualitative, and Review cluster provides the broader interpretive and normative foundation for ML research in finance. Rather than focusing exclusively on algorithmic performance, these studies examine AI adoption, organizational readiness, governance, ethics, trust, and regulatory implications. Qualitative and conceptual research emphasizes that successful AI implementation depends not only on technological sophistication but also on human resources, organizational culture, institutional capacity, and regulatory frameworks. This perspective is particularly important for avoiding the overgeneralization of findings from developed financial markets to emerging economies.

Overall, the seven clusters demonstrate a clear evolution in banking ML research. The field initially emphasizes predictive accuracy, credit risk, fraud detection, and customer analytics, before expanding toward deep learning, ensemble methods, anomaly detection, cybersecurity, privacy, federated learning, and ethical AI. This evolution suggests that the future of ML in banking will depend not only on increasingly sophisticated algorithms but also on their adaptability, explainability, security, privacy protection, fairness, and alignment with financial governance and resilience.
Vosviewer Analysis Results



Picture 1. Network Visualization of The Evolution of Machine Learning in Banking

This network visualization illustrates the relationship between the research theme between machine learning and the banking/finance sector which is analyzed using VOSviewer. Each node represents a keyword, the size of the node indicates the level of frequency of occurrence, while the connecting line reflects the strength of the relationship or co-ocurence between topics or clusters.

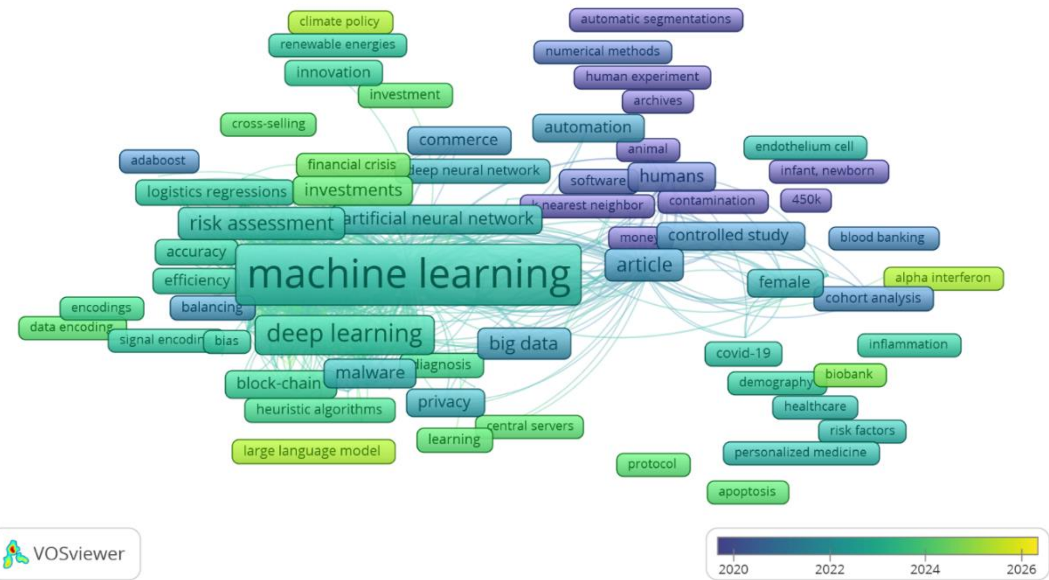
At the center of the network, machine learning emerged as the largest and most dominant node, signaling its role as the main foundation in various cross-sectoral studies, especially banking. These nodes are closely connected to deep learning, artificial neural networks, and big data, which shows that deep learning methods and large-scale data utilization are becoming key approaches in modern financial analysis.

In the context of banking, clusters related to risk assessment, financial crisis, and investments show how machine learning is used for risk management, financial crisis detection, and investment decision-making. The presence of algorithms such as logistic regression, adaboost, and nearest neighbor confirms that both classical methods and advanced models are used simultaneously in banking research.

Other relevant clusters show the linkage between machine learning and issues of efficiency, accuracy, and bias, reflecting concerns about the quality of predictive models as well as the ethical and ethical challenges of algorithmic justice in the digital financial system. In addition, the emergence of topics such as blockchain, privacy, and malware signals an increased focus on data security, privacy protection, and cyber risk in banking's digital transformation.

Interestingly, the network also shows cross-disciplinary connections with the fields of health, demographics, and covid-19, which shows that the development of machine learning methods in banking is also influenced by methodological advances from other sectors, especially in data analysis and risk modeling.

Overall, this visualization confirms that research on banking and machine learning is interdisciplinary, with machine learning as the innovation hub that connects risk analysis, investment, financial stability, data security, and data-driven decision-making. These findings reinforce the urgency of developing policies and governance frameworks that are adaptive to the use of machine learning technology in the modern banking system.



Picture 2. Overly Visualization of The Evolution of Machine Learning in Banking

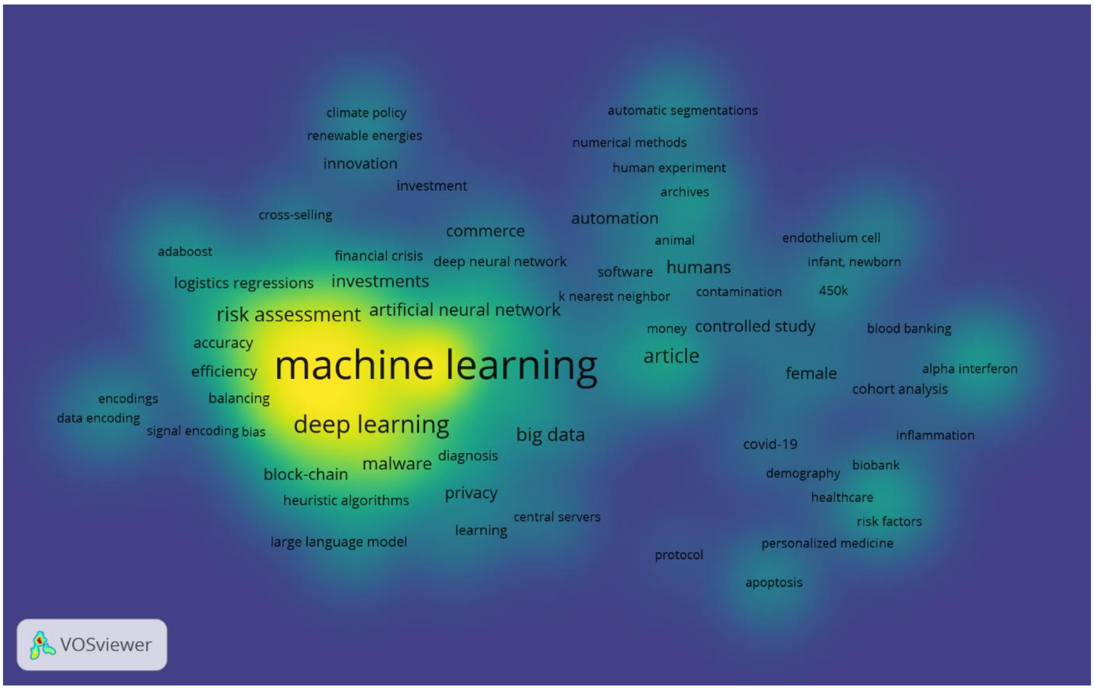
This visualization overlay illustrates the temporal development (time trends) of research that links machine learning to the banking and financial sectors. The colors on each node represent the average year of publication, where darker colors (blue–purple) indicate an earlier developing topic, while green to yellow denotes relatively new and developing themes.

In the initial period (around 2020–2021), the research was dominated by basic methodological topics such as artificial neural networks, logistic regression, nearest neighbors, and early applications of machine learning in risk assessment, financial crisis, and investment analysis. This shows that the initial phase of the research focuses on exploring the capabilities of machine learning to improve the accuracy of risk prediction and the stability of the banking system.

Entering the medium period (2021–2023), the color of the nodes began to shift to green, signaling a growing interest in more complex approaches such as deep learning, big data, and deep neural networks. In this phase, the research emphasizes not only accuracy, but also model efficiency, bias handling, and optimization of data-driven decision-making in banking activities such as cross-selling, investment management, and credit scoring.

In the latest period (2023–2025), the visualization overlay shows the emergence of topics with the lightest colors (bright green to yellow), such as large language models, blockchain, privacy, malware, and cyber risk. This indicates a shift in research focus towards digital transformation of banking, financial system security, and ethical and data governance challenges in the application of machine learning. In addition, the linkage with cross-sector issues such as healthcare, covid-19, and demography reflects the wider adoption of an interdisciplinary machine learning approach.

Overall, this visualization overlay confirms that the trend of banking and machine learning research has evolved from conventional predictive approaches to more sophisticated, adaptive, and security-oriented and data governance models. These findings show that future research will focus not only on model performance, but also on the resilience of the banking system, privacy protection, and the sustainability of financial technology innovation.



Picture 3. Density Visualisasi of The Evolution of Machine Learning in Banking

This density visualization was used to identify the level of dominance and intensity of the research theme in the banking and machine learning study. In this visualization, the increasingly light colors (bright yellow–green) indicate areas with high keyword density, while blue to dark green indicates a topic that is less dominant or still limited in the literature.

The visualization results show that machine learning is the most dominant theme, characterized by the highest brightness level and central position on the map. This confirms that machine learning is the main axis in the development of modern banking research. Around the main node, deep learning, artificial neural networks, and risk assessment also come out very brightly, indicating that deep learning approaches and risk analysis are the main and most intensely researched focus in the banking context.

Relatively high density is also seen in the topics of accuracy, efficiency, logistic regression, and investments, which show great attention to improving the performance of predictive models and their application in financial and investment decision-making. In addition, the existence of big data in well-lit areas indicates the important role of large-scale data in strengthening the application of machine learning in the banking sector.

In contrast, lower-brightness topics, such as blockchain, large language models, privacy, malware, and central servers, were in darker areas. This indicates that these issues are still relatively less dominant or in the early stages of development in the banking and machine learning literature, although they have great potential to develop in the future.

On the other hand, clusters related to health and biomedicine (e.g. covid-19, biobank, healthcare, and cohort analysis) also appear less bright and separate from the density center. This condition shows that the topic is more cross-disciplinary, with methodological contributions to machine learning, but is not mainstream in banking studies.

Overall, this density visualization confirms that current banking and machine learning research is still very focused on method development, model accuracy, and risk analysis, while new issues such as cybersecurity, data privacy, blockchain, and large language models are still not the dominant themes. These findings open up further research space, especially to integrate aspects of banking system resilience, data governance, and digital security in the development of machine learning in the financial sector.

Discussion

The findings demonstrate that research on machine learning (ML) in banking has evolved from a predominantly predictive and performance-oriented paradigm toward a broader framework emphasizing adaptability, security, privacy, explainability, and responsible AI governance. The identification of seven major clusters indicates that ML is no longer limited to conventional credit-risk modeling but has become an increasingly integrated component of financial decision-making and banking resilience.

The dominance of the Supervised Machine Learning for Credit Risk, Fraud, and Churn cluster confirms that prediction remains the central function of ML applications in banking. Logistic Regression, Decision Tree, Random Forest, and boosting algorithms continue to be widely used because they provide a balance between predictive capability, computational efficiency, and practical implementation. This finding suggests that technological sophistication does not necessarily imply the replacement of conventional models. Instead, traditional statistical and ML approaches remain relevant, particularly in highly regulated banking environments where interpretability and model validation are essential. This is consistent with the broader literature showing that ML can improve financial risk prediction while maintaining practical relevance when model transparency and robustness are considered (Warin & Stojkov, 2021; Rodríguez et al., 2024).

The findings further indicate that data quality and data structure may be as important as algorithm selection. The recurring emphasis on feature engineering, feature selection, and imbalanced data demonstrates that predictive performance is strongly influenced by how financial data are prepared and represented. This is particularly important for fraud and default prediction because minority events are relatively infrequent but economically consequential. Therefore, relying solely on accuracy can produce misleading conclusions. The increasing use of recall, F1-score, AUC-ROC, and other risk-sensitive metrics reflects a methodological shift toward evaluating whether models can effectively identify critical financial events rather than merely maximize overall classification accuracy.

The emergence of the Deep Learning and Hybrid ML–DL cluster indicates a second stage of methodological development. While supervised ML remains dominant, deep learning is increasingly employed to address the sequential, nonlinear, and high-dimensional characteristics of modern financial data. RNN, GRU, CNN, autoencoders, and Transformer architectures provide opportunities to capture temporal dependencies and latent representations that may not be adequately represented by conventional feature-based models. However, the findings suggest that deep learning should not automatically be regarded as superior. Its practical adoption remains constrained by computational requirements, large data requirements, and limited interpretability. Consequently, hybrid ML–DL models represent an important compromise between predictive performance and the explainability required in banking environments.

The Ensemble Learning and Imbalanced Data Handling cluster reinforces this argument by demonstrating that improving financial ML systems requires methodological attention beyond algorithm complexity. Ensemble learning and resampling techniques improve the ability to detect rare but consequential events, particularly fraud and default. This finding has important implications for banking risk management because a model that achieves high overall accuracy while failing to identify a small proportion of high-risk customers may generate substantial financial losses. Thus, future research should prioritize risk-sensitive predictive performance and model robustness rather than accuracy as the primary objective.

The Unsupervised Learning and Customer Segmentation cluster expands the role of ML from prediction toward exploration and discovery. Unlike supervised learning, unsupervised techniques can identify previously unknown customer profiles and behavioral patterns. This is strategically important because customer heterogeneity cannot always be represented through predefined risk categories. The findings therefore suggest that clustering can function as an upstream analytical process that supports subsequent supervised modeling, personalized financial services, customer retention, and financial inclusion. This creates opportunities for more integrated ML architectures combining exploratory and predictive analytics.

Another important development is the emergence of Anomaly Detection and Cybersecurity in Banking. This cluster demonstrates that the risk landscape of banking has expanded beyond traditional credit and market risks toward digital and cyber risks. The increasing dependence on mobile banking, digital payments, cloud infrastructure, and interconnected financial platforms creates vulnerabilities that cannot always be addressed through static rule-based systems. ML-based anomaly detection provides a more adaptive approach by identifying deviations from normal behavior. This finding is particularly significant because cybersecurity threats can generate consequences extending beyond individual institutions to operational continuity and confidence in the broader financial system.

The Privacy-Preserving, Federated Learning, and Ethical AI cluster represents perhaps the most important conceptual transition identified in the literature. Earlier ML research largely evaluated models according to predictive accuracy and computational efficiency, whereas recent research increasingly considers whether AI systems are trustworthy, explainable, fair, secure, and legally accountable. Federated learning is particularly relevant because it allows institutions to collaborate in model development without directly centralizing sensitive customer information. At the same time, issues of algorithmic bias, explainability, data governance, and consumer protection demonstrate that technological innovation cannot be separated from institutional and regulatory considerations (Černevičienė & Kabašinskas, 2024; Fundira & Mbohwa, 2025).

The Conceptual, Qualitative, and Review cluster complements the technical clusters by emphasizing that AI adoption is a socio-technical process. The effectiveness of ML in banking depends not only on algorithms but also on organizational readiness, human resources, institutional culture, regulatory frameworks, and stakeholder trust. This perspective is particularly relevant for emerging economies, where technological infrastructure, digital literacy, regulatory capacity, and financial-market structures may differ substantially from those of developed economies. Therefore, future studies should avoid treating technological adoption as context-independent.

Taken together, the findings reveal a research gap between technological capability and institutional readiness. Although predictive analytics and deep learning have received substantial attention, emerging topics such as privacy, cybersecurity, explainability, fairness, federated learning, large language models, blockchain, and data governance remain comparatively less developed. This indicates that the next generation of banking ML research should move beyond the question of "Which algorithm provides the highest accuracy?" toward broader questions concerning whether an AI system can be trusted, governed, secured, explained, and sustainably implemented.

Accordingly, the future research agenda should emphasize the integration of predictive analytics, cybersecurity, privacy preservation, explainable AI, ethical governance, and financial resilience. Such integration would contribute to the development of banking intelligence systems that are not only accurate but also adaptive, secure, transparent, inclusive, and institutionally sustainable. This evolution ultimately positions machine learning not merely as a technological instrument for improving bank performance, but as an increasingly important component of modern financial risk governance and systemic resilience.

Conclusion

The literature review shows that machine learning has become an important analytical instrument in banking, particularly for credit risk, fraud detection, customer churn, financial forecasting, and cybersecurity. The VOSviewer analysis indicates a shift from conventional supervised learning toward deep learning, ensemble methods, anomaly detection, privacy-preserving learning, and ethical AI. However, predictive accuracy remains the dominant research focus, while issues of explainability, privacy, fairness, financial stability, and governance are still developing. Therefore, future banking ML research needs to integrate predictive performance with responsible AI and broader financial resilience considerations. This study has several limitations. First, the literature mapping depends on the selected database, keywords, publication period, and inclusion criteria, which may exclude relevant studies indexed in other databases. Second, the VOSviewer analysis primarily captures keyword co-occurrence and bibliometric relationships and therefore cannot fully assess the methodological quality or empirical validity of individual studies. Third, differences in datasets, algorithms, evaluation metrics, and banking contexts make direct comparison of findings across studies difficult. Future research should focus on developing dynamic and explainable machine learning models that integrate banking-specific, customer-level, and macroeconomic variables. Greater attention should also be given to financial stability, cybersecurity, privacy-preserving learning, algorithmic fairness, and emerging economies. Hybrid ML–DL and federated learning approaches also provide promising directions for developing more accurate, adaptive, secure, and institutionally responsible banking decision-support systems

AUTHOR CONTRIBUTIONS

Conceptualisation, Aprizal, A and Danavia, A.; Methodology, Aprizal, A.; Investigation, Danavia, A; Analysis, Danavia, A.; Original draft preparation, Aprizal, A.; Review and editing, Danavia, A.; Visualization Danavia, A.

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CONFLICTS OF INTEREST

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