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Machine Learning in Banking Risk Management: Mapping a Decade of Evolution

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Abstract
Machine learning is widely used to transform risk management activities in the banking sector through advanced data analysis methods. Banks use statistical and rule-based techniques to perform risk management operations. However, such methods may be limited by their ability to model non-linear relationships and high dimensional financial data. Machine learning can help organisations forecast risks, put in place flexible plans to manage those risks and put in place an effective risk management framework. This paper discusses the evolution of machine learning techniques in risk management over the last ten years and their application in managing credit risks, market risks, operational risks, and liquidity risks.

The current review focuses on various machine learning algorithms that can be applied by banks to enhance their risk management efforts. These include artificial neural networks, support vector machines, decision trees, random forests, ensemble learning techniques, and deep learning techniques. In particular, the review addresses the advantages that banks can obtain from applying machine learning algorithms in risk management operations. Specifically, machine learning can improve banks' ability to predict risks, detect frauds, and identify anomalies. Although the capabilities of machine learning are quite promising, some of the challenges encountered include those related to interpretability, data quality issues, model risks, algorithmic biases, and regulation issues. The review has also revealed gaps in research areas such as liquidity risk, explainable artificial intelligence, and integration of machine learning into the banking risk management framework. The study indicates that despite machine learning playing a vital role in enhancing the predictive power of risk models, successful application of this technology can only be sustained through striking a reasonable balance between sophistication and regulation.

This study adds value to the emerging literature on the role of artificial intelligence in finance by offering a comprehensive review of machine learning in various areas of banking risk management and identifying areas of future research.

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1. Introduction

Banking risk management is still considered among the most essential components of the finance industry due to the volatile nature of the financial environment within which banks function. They face constant risks of both internal and external origin, including market volatility, loan defaults, cybersecurity threats, liquidity concerns, and regulatory risks. The 2007–2008 financial crisis highlighted the problems inherent in existing risk management practices, proving their ability to cause serious financial instabilities and even lead to the occurrence of economic catastrophes (Gorton & Metrick, 2012) [16]. This situation

made financial authorities introduce more stringent requirements towards the efficiency of risk management systems and practices applied by financial organizations.

Conventional risk management techniques include statistical methods, expert systems, and rules-based procedures such as logistic regression analysis, value at risk calculations, stress testing, and other credit scoring methodologies. While all of them are valuable, they still have some limitations, such as inability to detect non-linear relations, hidden patterns, and dynamics of the financial market. The growing process of digitalization of bank operations has added additional pressure towards developing more sophisticated analytics which would be able to analyze huge amounts of structured and unstructured financial data instantaneously (Leo *et al*., 2019) [20].

One of the major technological advances in modern financial analytics is machine learning. It is associated with several advantages, including the capability of learning and improving experience without prior programming. This allows machine learning algorithms to find hidden relationships and make predictions based on historical data. Unlike traditional statistical methods, machine learning algorithms do not depend on any predetermined model and are capable of constantly learning new data patterns. Thus, machine learning has become an increasingly attractive choice for bank risk management in areas such as credit scoring, fraud detection, market forecasting, liquidity management, and operational risk management (Milojević & Redzepagic, 2021) [24].

Machine learning algorithms are now being applied to bank risk management practices increasingly. In particular, numerous research papers show that machine learning algorithms surpass traditional methods in terms of predictive power and performance, particularly in nonlinear and multidimensional financial environments (Bhatore *et al*., 2020) [9]. Deep neural networks, ensembles, and support vector machines demonstrate high efficiency in financial anomaly detection, forecasting the borrowers' behavior, and fraud detection. However, at the same time, more financial organizations resort to automated solutions for the purpose of risk management and decision making in a timely fashion.

Although machine learning has demonstrated considerable promise in improving financial risk management, its adoption across banking remains uneven due to challenges related to interpretability, data quality, regulatory compliance, and ethical concerns. Furthermore, whilst there has been previous work on reviewing machine learning within the banking industry (e.g., Leo *et al*., 2019, Milana and Ashta, 2021) [20], this review seeks to provide additional information, to better understand how machine learning is used across different risk areas. This review will focus on credit, market, operational and liquidity risk, unlike previous work by Leo *et al*. (2019) [20] which gives an overview. Emerging trends will be discussed such as explainable AI, integrated risk management, real-time analytics and regulatory governance. Accordingly, this review synthesizes recent evidence on the application of machine learning in banking risk management, critically evaluates the strengths and limitations of existing models, and identifies future research directions toward the development of more integrated and robust risk management frameworks.

2. Overview of Risk Management in Banking

Risk management in the banking industry has seen tremendous changes over the past several decades due to the increasing interconnection and complexity of financial systems driven by technological advances. Financial organizations conduct their activities in highly uncertain environments, which are susceptible to financial market turbulence, behaviors of borrowers, business procedures, and regulations. In such circumstances, risk management has become an indispensable element for ensuring the stability of financial institutions and the safety of their customers and investors.

Regulatory measures like Basel requirements that were launched in the aftermath of the global financial crisis, further reinforced the focus of financial institutions on risk management practices. This creates requirements around capital adequacy and liquidity which can help banks become prepared in case they experience any negative economic shocks through stress-testing (Basel Committee on Banking Supervision [BCBS], 2023) [8]. This has put pressure on financial institutions to use analytical tools to improve their risk prediction and management.

Historically, traditional risk management frameworks in the banking sector have utilized various econometric models, such as linear regression, logistic regression, discriminant analysis, and simulation approaches. These methods have gained widespread popularity due to their explanatory power. For instance, logistic regressions have become commonly applied to credit scoring since they allow providing reliable probability estimates and have higher interpretability compared to other statistical methods in use by regulators and financial professionals (Horcher, 2005) [18]. Another good example is Value at Risk (VaR) models which started to be widely employed to estimate potential losses in trading positions in case of normal market operations (Horcher, 2005) [18].

Traditional methods have many flaws as was seen in modern financial systems. Many traditional statistical models make assumptions based on historical data. Financial markets are also very volatile and can be subject to extreme events. This means that the traditional models cannot accurately reflect what may happen during these events (Danielsson, 2002) [13]. During the 2007-2008 financial crisis, risk modelling and stress testing were seen to be flawed within banks which led to an underestimation of potential losses (Basel Committee on Banking Supervision [BCBS], 2009) [7].

Another important trend which became especially vivid recently related to the rapid development of digital banking and financial technologies. Thus, nowadays, banks are dealing with vast amounts of data generated during the course of operation. The classical tools of analysis are frequently unable to process such datasets in real-time scenarios effectively. Thus, modern organizations have started shifting towards machine learning techniques, which allow analyzing massive datasets while uncovering some concealed patterns and complex relationships.

Machine learning is a branch of artificial intelligence that enables computers to learn patterns from data and improve their predictions without being explicitly programmed with specific rules for every task. Unlike conventional models that depend on mathematical assumptions and equations, machine learning techniques discover patterns within data,

continuously upgrading themselves when encountering new information (Pallathadka *et al*., 2023) [25]. It means that such techniques will be effective when applied to the ever-changing financial landscape.

There are several categories of machine learning models, namely supervised learning, unsupervised learning, reinforcement learning, and ensemble learning. The first group of models is based on training processes using labeled datasets whose outcomes are defined in advance. Such models are commonly employed within the banking industry in tasks like predicting default behavior, scoring credits, and detecting fraud due to the presence of historical financial results. Some common supervised learning methods used include Support Vector Machines (SVM), Decision Trees, Random Forests, Logistic Regression, and Artificial Neural Networks (ANNs). Logistic regression, a traditional statistical method, is also widely used as a baseline machine learning model for classification tasks (Kubat, 2017) [19].

Some of these categories may overlap because they describe different aspects of machine learning. For example, Random Forests are Supervised Learning models that use Ensemble methods to improve the predictive ability by combining many Decision Trees. This means they should fall into the supervised learning section but also can be highlighted as using an ensemble method. Logistic Regression can be seen to be both a statistical model and a machine learning algorithm.

The main advantage of Support Vector Machines is that it is well known to be effective in solving the problem of high-dimensional datasets in finance, as well as the problem of nonlinear classification of observations. SVM builds an optimal hyperplane, which helps to distinguish data based on different categories and maximize the distance between observations. Thus, the method enables achieving good predictions despite complex environments where the data structure is nonlinear and noisy (Cortes & Vapnik, 1995) [11].

The use of decision trees and random forests has been very widespread due to their flexible structure and relatively strong predictive power in banks. Decision Trees are based on splitting observations into several categories based on feature divisions. Random forests can help to overcome the problem of overfitting in case of using Decision Trees independently since the former combines many Decision Trees (Breiman, 2001) [10].

Another group of machine learning models that are widely used in financial risk management is Artificial Neural Networks. These are computer systems that replicate how a brain works by modeling a series of interconnected artificial neurons to learn from massive amounts of data through complex non-linear relationships. The deep-learning variants like LSTM network and Recurrent Neural Network (RNN) models work effectively in the sequential and time-series problems related to finance because they have the capability of retaining long-term temporal relationships (Dixon *et al*., 2020) [14].

Unsupervised learning techniques are different from the supervised techniques because they operate on unlabeled data sets. Unsupervised techniques are usually utilized for finding anomalies in financial transactions, customer segmentation, or detecting any frauds in banking activities. Clustering algorithms like k-means clustering model are useful to find out any clusters in datasets for identifying any anomalies in transaction behaviors or operations without any labeled data.

Ensemble methods provide a way of improving the prediction performance by combining multiple machine learning models. Techniques such as Random Forests and Gradient Boosting have been used within credit scoring. Lessmann *et al*. (2015) [21] conducted a benchmark comparison using 41 different classification algorithms on 8 real world credit scoring data sets. They found that several classifiers provided better performance than logistic regression. In particular, the heterogeneous ensemble classifiers performed well.

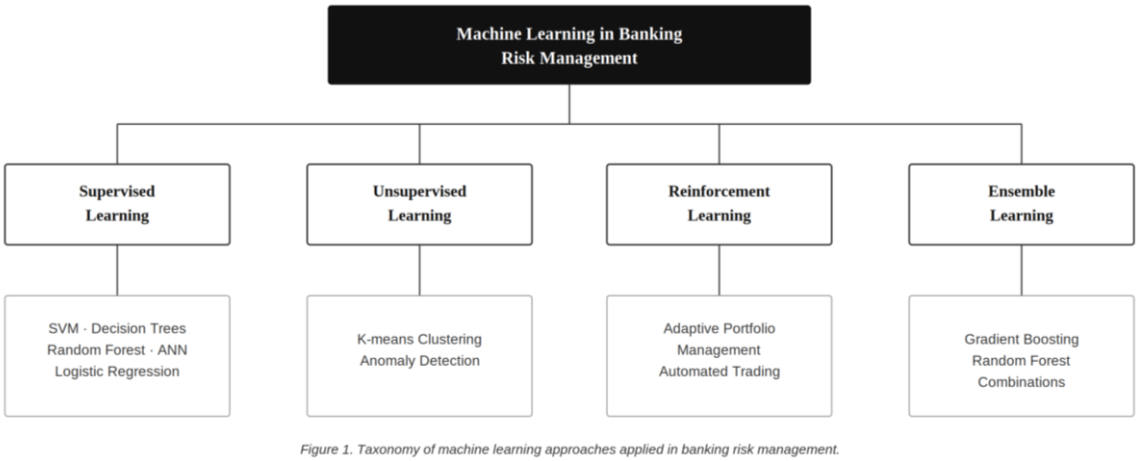


Figure 1. Taxonomy of machine learning approaches applied in banking risk management.

Fig 1: Taxonomy of Machine Learning Approaches in Banking Risk Management

There has been significant attention in the financial literature regarding the increasing use of machine learning algorithms within the banking sector. Empirical studies have investigated how well machine learning fits credit scoring and default prediction models compared to traditional statistical models such as logistic regression. For example, Aniceto *et al*. (2020) [6] looked at the performance of several machine learning models using a sample of over 250,000 loan records from a financial institution in Brazil. The results showed that Random Forest and AdaBoost had the best performance. Furthermore, Alonso-Robisco and Carbó (2021) [4] also found that the credit default classification and calibration was improved when using machine learning versus logistic regression models using data from a large Spanish bank. They later conducted a study estimating that substituting LASSO with XGBoost could reduce regulatory capital requirements by between 12.4% to 17% when using the Internal Ratings-Based approach (Alonso-Robisco &

Carbó, 2022) [5]. Recently, there is evidence showing that XGBoost provided excellent out-of-time performance regarding corporate credit risk in Brazil (Pinto *et al*., 2024) [26]. This suggests that machine learning models can improve performance and provide added value within risk management decisions within certain areas of banking. However, the success of using machine learning will depend on the dataset, how it is validated and the risk metric being used.

Table 1: Selected empirical studies comparing machine learning models in banking risk management

Study	Risk type and data	Models compared	Main finding
Aniceto *et al*. (2020) [6]	Credit risk; more than 250,000 borrowers from a Brazilian financial institution	Logistic regression, Random Forest, AdaBoost, Decision Trees, SVM	Random Forest and AdaBoost performed better among the models examined.
Alonso-Robisco and Carbó (2021) [4]	Credit risk; anonymised data from a major Spanish bank	Logistic regression, LASSO, CART, Random Forest, XGBoost, deep neural networks	ML models outperformed logistic regression in classification and calibration, although more complex models did not always perform better.
Alonso-Robisco and Carbó (2022) [5]	Credit default prediction; public credit-default dataset	LASSO, CART, Random Forest, XGBoost, deep learning	XGBoost and Random Forest performed well after considering model risk. The authors estimated potential regulatory capital savings of 12.4%–17% from using XGBoost instead of LASSO.
Pinto *et al*. (2024) [26]	Corporate credit risk; financial and economic indicators from Brazilian wholesale firms	XGBoost and logistic regression, within a broader supervised ML analysis	XGBoost achieved a reported out-of-time ROC result of 0.97, although accuracy was 0.59, illustrating why multiple evaluation metrics are important.

However, the integration of machine learning into banking raises many issues. For instance, one of the primary issues is the difficulty in comprehending how certain advanced machine learning models make decisions. Deep learning models are complicated black boxes whose inner workings are hard to understand (Giudici & Raffinetti, 2023) [15]. This creates conflicts with regulatory obligations for transparency and accountability in financial decision-making processes. Other problems to consider include data quality problems, cyber security risks, algorithmic bias, and model risk due to overfitting and poor generalization in crises. Financial institutions thus must weigh the advantages of predictive analytics offered by machine learning against the necessity for good governance, fairness, and regulatory compliance.

In conclusion, the literature reveals that the use of machine learning has become increasingly significant in contemporary banking risk management because of the capability of the technology to handle massive amounts of data, uncover complex financial patterns, and enhance predictive decision-making. Nevertheless, the success of these technologies is not only dependent on the algorithms but also on data quality, governance frameworks, and regulatory compliance processes.

3. Machine Learning Applications in Modern Banking Risk Management

There is an increasing trend of using Machine Learning (ML) in modern banking to help manage risks such as fraud detection, market prediction, risk assessment and regulatory compliance. As technological capabilities and data analytics have increased in recent years, banks have been able to utilise larger data sets to detect patterns in data. The financial risk management literature has identified many areas banks are applying ML to in relation to risk management. Areas include credit risk, market risk, fraud detection and others. Challenges also arise in relation to model readability, data quality and implementation (Mashrur *et al*., 2020; Milana & Ashta, 2021) [22, 23]. However, some banks may benefit more than others.

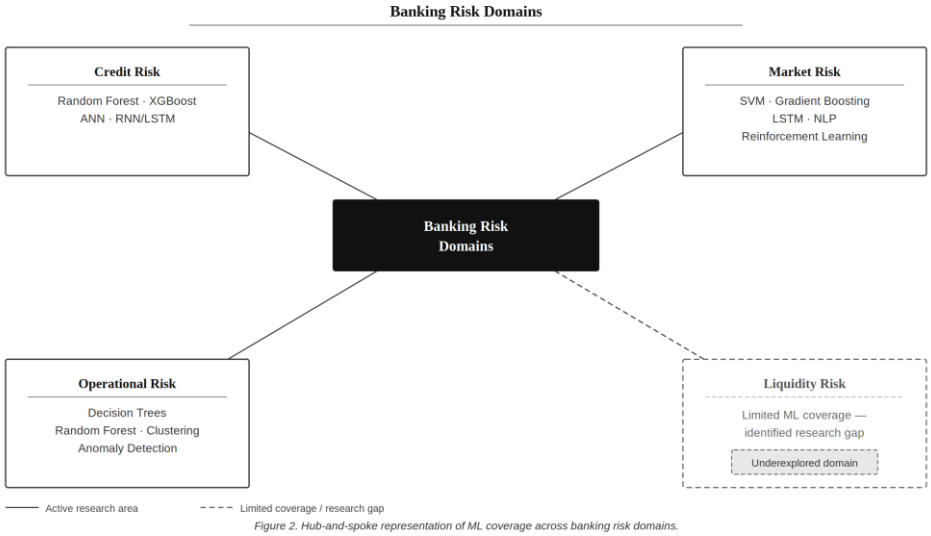


Fig 2: Mapping of ML Techniques in Relation to Risk Areas in Banking

3.1. Credit Risk Management and Default Probability

Credit risk management is one of the most researched areas in relation to ML in banking. Predictive models are used throughout this area to aid credit scoring, determining default probabilities and assessing creditworthiness of borrowers. Logistic regressions are a common type of model used to predict credit risk. However, many alternative models have been tested.

Common models include Random Forests, Support Vector Machines (SVM), Gradient Boosting Machines, Artificial Neural Networks (ANN) and Extreme Gradient Boosting (XGBoost). A study undertaken by Lessmann *et al*. (2015) [21] tested 41 classification algorithms on 8 real-world credit scoring data sets. It was found that "several classifiers significantly outperformed logistic regression" (Lessmann *et al*., 2015) [21]. It was also discovered that heterogeneous ensembles performed well. This demonstrates that ML can be used to improve credit risk predictions, however it will depend on the data set, metric and validation.

Alternative data sources have been seen in credit scoring to add extra information. This can involve analysing digital payments and transaction data. AI has been linked to providing opportunities to reach new customers within financial services (Milana & Ashta, 2021) [23]. However, this will depend on data availability, data representativeness and mitigating any bias.

Sequntial models such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) can be explored. This would be useful if you wanted to analyse how credit risk increases due to changes in behaviour from borrowers overtime. However, it should be tested in comparison with traditional models (Mashrur *et al*., 2020) [22].

There are concerns around fairness and transparency when using ML to determine credit risk. Therefore, banks should consider how interpretable the model is, whether it causes bias and if it is suitable for making regulatory and business decisions (Milana & Ashta, 2021) [23].

3.2 Market Risk Forecasting and Portfolio Management

Market risk involves fluctuations in financial factors such as equity prices, interest rates and exchange rates. Many studies have looked at using ML to predict financial data, measure risk and allocate portfolios. The quantitative finance literature has identified that ML can be used in financial prediction, trading and optimising portfolios. It is important to choose the correct method based on the task (Rundo *et al*., 2019) [28].

Common models include Support Vector Machines, trees and Neural Networks. These models can be used to predict market movements, calculate Value at Risk and predict Expected Shortfall. Performance should be measured using the correct validation and risk specific back testing methodologies (Mashrur *et al*., 2020) [22].

Deep learning techniques have also been explored. For example, Qiu *et al*. (2024) [27] analysed recurrent neural network models to jointly predict VaR and ES. Six time series were used to compare the models with benchmark models. Overall, generally the proposed stateful recurrent models outperformed the benchmarks. This shows that recurrent neural networks can be valuable in financial tail risk estimation, however it does not necessarily mean they outperform in all markets.

Natural language processing can be used to extract information from text. This could include analysing financial news, company announcements and economic reports. This can provide sentiment indicators (Milana & Ashta, 2021; Rundo *et al*., 2019) [23, 28].

Reinforcement learning has also been investigated. This is a type of learning that differs to supervised learning as it uses reward to optimise actions. This can be useful in situations where decisions need to be made sequentially such as portfolio allocation. However, just because a model performs well in simulations it doesn't necessarily mean it will provide reliable results in practice. Transaction costs, market changes and risks involved in implementing learnt trading strategies must be considered (Rundo *et al*., 2019; Mashrur *et al*., 2020) [22, 28].

Overall ML can provide alternative methods of assessing market risk. However, it needs to be validated thoroughly, using the correct risk metrics and have the ability to adapt to changes in markets. Using hybrid models could be explored to find a good balance between performance, interpretability and risk management.

3.3. Operational Risk and Fraud Detection

Risk management within banks has been improved with the use of Machine Learning. As banks deal with large amounts of transactions everyday it can become difficult to identify any issues manually. However Machine Learning can be used to constantly monitor transactions and identify any anomalies early (Mashrur *et al*, 2020) [22].

One of the uses of Machine Learning in banking is fraud detection. Supervised learning can be trained using past transactions, using techniques like Decision Trees, Random Forests, Gradient Boosting Machines and Neural Networks. The models look at different aspects of the transactions such as amount, customer behaviour, device information, geographical information, frequency and spending patterns to identify fraudulent transactions (Mashrur *et al*, 2020) [22].

Fraud detection can also be done using unsupervised learning. This can be used when there isn't enough labelled examples of fraudulent transactions. Clustering and anomaly detection can identify which transactions don't fit a pattern. However this does not mean it will always be fraudulent and would need to be looked into further (Mashrur *et al*, 2020) [22].

The use of ML in AML and regulatory compliance helps to monitor any suspicious transactions automatically. Machine learning models based on natural language processing allow to detect any suspicious activities through automatic analysis of descriptions of transactions, client's emails and other documents that can be used to identify potential money laundering activities.

Machine learning can provide benefits when it comes to Cyber Security. Security systems can look through network traffic, system logs and user activity to identify any potential threats. These threats could be phishing, malware, intrusion, unauthorised access and insider threats. Deep learning can be used to identify any anomalies within large sets of data (Ahmed *et al*, 2025) [1].

Machine learning can help improve efficiency within operations by identifying patterns in failure, predicting resources and automation. This can help financial institutions improve their monitoring of operations and resources but depend on the quality of the data, reliability of the model and how well it integrates with current systems (Mashrur *et al*, 2020) [22].

3.4. Liquidity Risk Management

Liquidity risk is defined as the risk that the bank will not be able to pay it's financial obligations when due without incurring unacceptable losses. Machine learning can be used to assist with liquidity risk management through using historical financial information to identify trends in cash flow and deposit withdrawal. This can help to allow banking institutions to look ahead and better manage their liquidity.

Machine learning techniques can be used to identify complex relationships between variables affecting liquidity. Compared to standard statistical methods. However, the success of these techniques depend on the quality of data, reliability of models and ability to adapt to changing financial situations. Therefore, machine learning should be used to compliment current liquidity risk management methods.

3.5. Emerging Trends in Machine Learning for Banking Risk Management

Recent advances in technology mean that ML can now be used for a variety of applications within risk management in the banking sector. However, ML will only provide real benefits if the quality of data and explainability, governance and integration of the technology is considered (Theodorakopoulos *et al*. 2025) [29].

Hybrid AI models apply ML alongside statistical/econometric and other models. This can allow organisations balance between the ML and traditional risk modelling. However there are no guarantees that ML will provide increased accuracy and explainability. The success of hybrid models will depend on what models are used along with the quality of data and whether they are validated properly (Theodorakopoulos *et al*. 2025) [29].

Using alternative data is also becoming a trend. Alternative data such as mobile phone data, digital data, application data and other sources can give extra insight into customers who may not have much historical credit data. Using alternative data can improve credit assessments but there are concerns around data privacy, data bias, sample representation and fairness within credit decisions (Alok *et al*. 2022) [3].

Cloud and big data technology can provide the infrastructure required to handle large amounts of structured and unstructured data. This can improve the frequency of risk assessments using ML. However, there will be risks when using cloud providers. There are concerns around data security, third party risk, service availability (Crisanto *et al*. 2024) [12].

Natural language processing allows financial institutions to extract information from documents. This could include classifying documents, monitoring regulatory publications, assisting with documentation, sentiment analysis and automating customer service processes. This can improve efficiency but it will depend on the quality of data and accuracy of models.

Explainable AI is also becoming a point of interest. As ML models become more complex they can be hard to understand. Explainable AI aims to make the output more understandable for risk managers, auditors and other stakeholders. Within the banking sector this can help with model validation, governance and ensuring decisions made have been reviewed. However, just because models can be explained does not mean they are fair, accurate or in line with requirements (Weber *et al*. 2024) [31].

Generative AI can help with a variety of processes within financial services. Large language models can be used to summarise reports, search internal knowledge, assist with compliance reviews, help staff and improve customer communication. This could also be used for risk analysis. However, the output must be properly validated. Generative AI can produce incorrect information and sensitive data. Therefore there must be proper human oversight, data protection and model governance in place (Crisanto *et al*. 2024) [12].

ML has evolved from being a niche technique to providing a wider capability. New technologies can help with identifying, predicting, monitoring and decision making around risks. However, model risk, explainability, data governance, cyber security and operational resilience must also be considered. In the future, ML within the banking industry will likely evolve to ensure models are more sophisticated and responsibly integrated into risk management and governance.

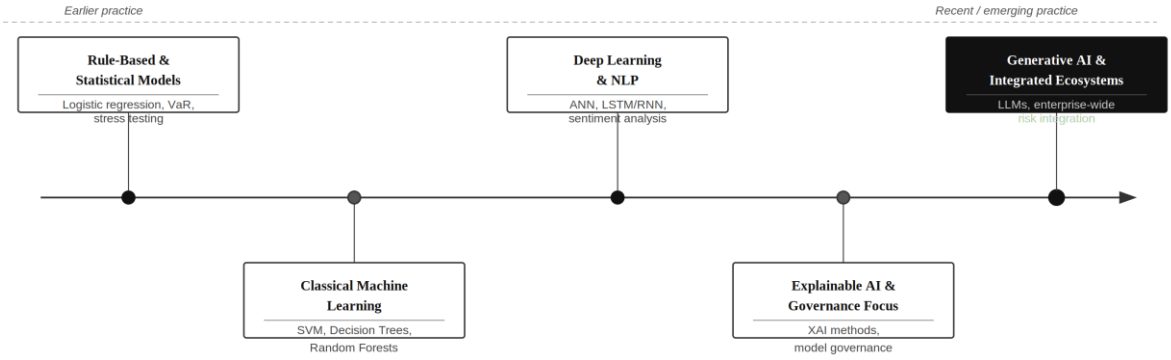


Figure 3. Chronological evolution of machine learning paradigms in banking and financial risk management.

Note. Author's own synthesis based on the literature on artificial intelligence in financial services, including Leo *et al*. (2019) [20], Herrmann and Masawi (2022) [17], and Aldasoro *et al*. (2024) [2].

Fig 3: A Decade of Evolution: From Rule-Based Models to Generative AI in Banking Risk Management.

4. Challenges and Research Gaps

Despite the rising popularity of machine learning applications in the banking sector, there are some challenges that hinder the complete implementation of ML solutions. They go far beyond model performance and include such aspects as explainability, data problems, cybersecurity issues, ethics, regulations, and organization preparedness.

4.1. Challenges

Model explainability is one of the most critical challenges. Modern models like deep learning algorithms can be considered "black boxes" since they can predict results very accurately but at the same time it is quite hard to interpret the logic behind those predictions. The problem becomes crucial for regulatory bodies, auditors, and risk managers since they should explain decisions about the approval of loans or any other financial operation. One of the possible ways of solving the problem is Explainable Artificial Intelligence (XAI), which allows understanding how models work. Unfortunately, most of the XAI methods are still not popular enough and are not used in banks (Giudici & Raffinetti 2023) [15].

The problem of data quality and availability remains important as well. Machine learning algorithms need much data for training and validation. Nevertheless, the data used in banking is often incomplete and contains inconsistencies, duplicates and historical biases. Furthermore, fraud detection and credit risk datasets are quite imbalanced since the amount of observations that are frauds or defaults is insignificant compared to the overall amount of cases. This could negatively affect the model accuracy if nothing is done about it. Moreover, there are strict privacy rules that restrict the exchange of information between companies.

Another issue related to the use of machine learning models in banking is cybersecurity. With more and more processes conducted with the help of such systems, the risk of a cyberattack increases. The adversarial attacks could influence the predictions of the ML models, thus causing inaccurate risk assessment and ignoring fraudulent transactions. Therefore, special attention should be paid to protecting ML models from the cyber threats.

Ethical issues also should be discussed. ML models could unconsciously support historical biases contained in training sets. It means that certain clients could be discriminated in the course of risk assessment and fraud detection processes. Thus, banks need to build a framework for governance that will encourage fairness, accountability, and transparency during all stages of AI development. Model validation, bias testing, and audits are increasingly becoming integral parts of the process of good governance of artificial intelligence. Lastly, one should pay attention to the problems associated with implementation. The use of machine learning solutions will imply heavy expenditure on technology, people, and organizational changes. Currently, many banks, especially smaller ones, still lack experts who could work with machine learning and the necessary finances for implementation.

Table 1: Key Challenges in Machine Learning Adoption for Banking Risk Management

Challenge	Description
Model Explainability	Deep learning models function as “black boxes,” complicating regulatory and audit requirements
Data Quality & Availability	Incomplete, inconsistent, or imbalanced datasets (e.g., rare fraud/default cases) reduce model accuracy
Cybersecurity Risk	Adversarial attacks can manipulate ML predictions, leading to inaccurate risk assessments
Ethical & Bias Concerns	Models may perpetuate historical biases, risking unfair treatment of certain clients
Implementation Readiness	High costs and shortage of skilled personnel limit adoption, especially at smaller banks

4.2. Research Gaps

Despite fast-growing research on machine learning in the banking industry, there are several gaps that should be covered by further studies.

The first of these gaps concerns the topics investigated by researchers in this field. So far, machine learning applications in credit risk management and fraud detection have drawn much interest from researchers. On the contrary, other types of risks, such as liquidity risk, strategic risk, reputational risk, and enterprise-wide risk management have not received sufficient attention. In this regard, further research may concern how machine learning models can be applied in these spheres.

Another issue that requires research is machine learning implementations in the banking environment. Most of current studies are concentrated on predictive accuracy, while the number of studies investigating implementation challenges is small. It would be beneficial for research in this area if more attention was paid to the problems banks may face implementing machine learning tools.

Finally, the problem of Explainable Artificial Intelligence needs to be explored further. Despite the fact that there is a general understanding that AI models should be explainable, the way of combining explainability and predictive performance is yet to be developed.

There was also a lack of research on machine learning applications in financial risk management across different areas. Current literature shows there has been an abundance of research done focusing on the Chinese financial sector and some European countries, however there were limited studies on other regions (Theodorakopoulos *et al*., 2025) [29]. A systematic review into machine learning applications in financial risk management in the internet industry showed that around two thirds of studies focused on the Chinese market (Machine Learning in Internet Financial Risk Management: A Systematic Literature Review, 2024) [31]. This does not mean that all research carried out on machine learning in banking risk management follows this trend. However this shows that research needs to be conducted across the globe and different areas of the world should be compared. Further empirical research could be carried out in developing economies to understand how factors such as different regulatory frameworks, financial inclusion, digital infrastructure and data availability affect the use of machine learning in banking risk management. Comparing developed and developing banking systems would help determine how generalisable the findings are.

Future research could address the issues of AI ecosystems. Today, bank risk management is becoming an ecosystem, which includes machine learning, cloud computing, blockchain, Internet of Things (IoT), and big data analysis. Studying the interactions between all these technologies in enterprise risk management could become another area of future research.

In general, machine learning has already proved to be a very promising technology in risk management for banks. But to use it successfully in the long term, the bank sector will need not only to continue advancing prediction algorithms, but also work on the challenges and gaps discussed above.

The evolution of machine learning in banking risk management will most likely be determined by digitalization, increasing volumes of data and the development of AI technologies in the future. Banking companies will shift from fragmented ML solutions towards integrated systems for enterprise risk management encompassing various types of risk, such as credit risk, market risk, operational risk and liquidity risk management.

At the same time, the spread of ML-based solutions in banking will be contingent upon successfully solving the problem connected with explainability, cybersecurity and data quality, as well as readiness of the workforce and regulatory issues. The concepts of explainable AI, ethical governance and regulation in the field of AI will gain increased significance, and cooperation between banks, regulators, technology vendors and universities will become more intensive.

Further academic work is required to focus on the problems associated with the creation of explainable AI and hybrid models combining machine learning and classical financial theory. In addition, research needs to be conducted around integrated risk management and multiple risk domains. Moreover, further studies need to explore practical applications of machine learning in banking, including organizational readiness, regulatory compliance, cybersecurity and new financial markets.

5. Conclusion

In recent years, machine learning has gained relevance for improving risk management practices in the banking industry. This literature review proved that ML techniques are used in many risk categories, namely credit, market, and operational risks, in which the use of predictive algorithms increases precision, allows decision-making in real time and supports fraud prevention and regulation compliance. The expansion of the usage of alternative data sources and learning methods has made possible additional opportunities for banking risk management.

There are still several limitations that prevent the extensive usage of ML. Model explainability, data quality, cybersecurity, ethical problems, and regulation compliance are still the challenges of ML techniques. Additionally, there are other risk areas that require additional attention such as liquidity, strategic risk management and enterprise-wide risk management.

Successful application of ML to banking requires not only the development of predictive algorithms but also proper governance and data management, experienced staff and responsible AI practices. Thus, the future researches must be focused on the development of explainable and reliable models of AI and the study of ML in new risk categories of banking.

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