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# Machine learning in banking risk management: Mapping a decade of evolution

Valentin Lennart Heß, Bruno Damásio *

Nova Information Management School (NOVA IMS), Universidade Nova de Lisboa, Campus de Campolide, 1070-312 Lisboa, Portugal

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ABSTRACT

The techniques used in banks' risk management are evolving as opposed to the process of risk management. It is necessary to respond to these market- and technology-driven changes appropriately. Innovative approaches are needed to overcome the limitations of traditional methods. Machine learning (ML) algorithms are suitable for dealing with the various risk types banks face. Academic literature focuses on applying ML in credit risk management. This article addresses market, operational, liquidity, and other risk types, with the objective to examine how ML algorithms predict, assess, and mitigate these risks and identify both their advantages and challenges. This article systematically reviews 46 recent studies and highlights the expanding role of ML in enhancing risk management strategies. The article has revealed that ML is adequately covered in the context of market and operational risk. The learning ability and predictive capabilities of artificial neural networks and other algorithms are promising for risk management. Our findings offer a concise overview of current ML applications for multiple risk types in banking, identifying research gaps, highlighting opportunities and challenges and providing actionable directions for further studies. By providing a focused overview of the expanding role of ML in banking risk management, we underscore the potential to strengthen the robustness of banks' strategies and practices.

## 1. Introduction

Machine learning (ML) has become a transformative force in banking risk management, evolving significantly over the last decade. This article addresses the broad implications of ML applications across various risk types in banking, highlighting the gaps left by previous research that primarily focused on credit risk. By exploring market, operational, and liquidity risks, this study aims to provide a wide-ranging overview of ML's potential to enhance risk management strategies, thus contributing to the stability and resilience of financial institutions.

In fact, banks face various factors and events, such as market volatility, credit defaults, operational failures, and regulatory changes that could harm their operational stability, profitability, or reputation. To prevent these threats, banks must identify, assess, and mitigate them by employing risk management practices to anticipate and respond to these challenges. Stable risk management is essential for a bank to deal with these challenges, especially in times of crisis. Effective risk management safeguards investors' interests, enhances trust, and ensures long-term sustainability in a dynamic environment. Risk management is subject to constant change, characterized by varying market conditions, regulations, and advances in practices and technology. This risk management evolution synergizes strongly with ML properties and developments. The implementation of ML techniques can have significant benefits on the quality and execution of risk management in comparison to classical approaches. By leveraging advanced pattern recognition, data analysis, and predictive modeling, ML allows banks to enhance their risk mitigation by predicting and treating potential threats (Leo et al., 2019). To maintain control over risks, banks employ various methods, tools, and techniques that increasingly leverage ML. These techniques include stress testing, risk assessment, portfolio analysis, setting risk limits, scoring systems, estimating Value at Risk (VaR) and Expected Shortfall (ES), and many more (Milojević & Redzepagic, 2021).

Several studies have intensively researched ML in risk management, and further developments are expected. The literature categorizes banks' risks into four major categories: credit, market, operational, liquidity, and other risk types (Milojević & Redzepagic, 2021). Most studies and literature reviews deal with the application of machine

* Corresponding author.
*E-mail address:* bdamasio@novaims.unl.pt (B. Damásio).

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learning in credit risk management, which is one of the most significant risks for banks (Bhatore et al., 2020; Chen et al., 2017; Shi et al., 2022; Tyagi, 2022). However, research is lacking in other risk areas (Leo et al., 2019). Since this finding, more research on other risk types has been done, and machine learning models have been trained and tested but not uniformly summarized. This research gap serves as a guideline for this study, leading to the following research question:

> **RQ**: How is machine learning utilized in scientific literature in dealing with market, operational, liquidity, and other risks within banking risk management?

The research objective is to identify application areas in risk management that can benefit from machine learning. Additionally, an objective is to develop a guideline for banks, showing which machine learning algorithms can be used in the respective areas and risk types. The methodology consists of a qualitative and quantitative approach. A systematic literature review (SLR) is conducted on scientific databases using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis framework (PRISMA), and the data is analyzed based on qualitative and quantitative aspects (Page et al., 2021). By following the proposed guidelines, a collection of scientific work is developed and evaluated on aspects such as used algorithms, risk categories, performance metrics, practical results, and more. This research will unveil the spectrum of machine learning capabilities in banking risk management. These findings will contribute to the ongoing academic discourse on cutting-edge technologies in the financial sector. The empirical results can help banks develop comprehensive guidelines for integrating machine learning into their risk management strategies. It may also uncover challenges and opportunities that inspire further research.

This study is structured as follows: The theoretical background information is covered in the second section, together with related work that highlights the study's relevance. This section provides a general overview of risk management in banks and explains the different types of risks. Additionally, machine learning is introduced, and the most important algorithms used in the banking sector are outlined. Section three deals with the research methodologies. A more detailed explanation of the systematic literature review approach is provided. Next, the answers to the research question are presented in the results section. The results are analyzed in more detail in the discussion section, and practical implications, limitations, and further research directions are pointed out and finally summarized.

## 2. Theoretical background

### 2.1. Risk management foundations

Financial institutions such as banks play a crucial role in society. They act as intermediaries for the circulation of money and credit in the economy and private households. Thus, they offer a place to store money and provide various other services, such as giving credit loans, mortgages, and many more amenities. Banks primarily contribute to a society's economic growth and stability by enabling lending, promoting investment, and supporting financial stability (Chockalingam et al., 2018). Banks are exposed to various internal and external risks, like those faced by ordinary companies. Risk can be defined as the probability of losses resulting from different events (Horcher, 2005). Risk management practices seek to protect the financial system from risks like credit defaults, market volatility, or operational and liquidity risks (Leo et al., 2019). However, a significant difference to regular companies is that risk-triggered failures in the financial system can lead to systemic crises, as was observed in the global financial crisis of 2007/2008. A failure in bank risk management led to one of the most significant financial crises of the last century. It happened due to banks accepting high risks in the form of risky mortgage loans, performing financial engineering, and poor regulation, which led to a collapse of the housing market and the global financial system (Gorton & Metrick, 2012). With the introduction of sophisticated risk management, banks nowadays seek to prevent such events from recurrence or better manage the consequences of these incidents. Risk management aims to protect assets, maintain liquidity, and ensure profitability and compliance by identifying, assessing, and managing different risks (Alazzabi et al., 2023). Therefore, banks' risk management is paramount for economic activity and existence in the market; thus, they must consider several influencing factors. Loan borrowers could fail to make their payments, market interest rates could change and affect bank loan values, banks' investments could lose value or human input errors, or fraud could affect the business (Apostolik et al., 2012). These examples show that banks must be prepared for several types of risks to be able to act according to the situation.

Due to the great importance of banks for society, they are subject to state regulations, which in Europe are defined by the frameworks Capital Requirements Directive (CRD IV) and Capital Requirements Regulations (CRR) of the European Parliament. This regulatory requirement package implements the Basel III framework (DEPC, 2023; DEPC 2023). The Basel III Framework is an international set of reforms published by the Basel Committee on Banking Supervision in response to the 2007/2008 financial crisis to enhance regulation, supervision, and risk management in the banking sector (Chockalingam et al., 2018). Basel III is a set of regulations that describes measures to strengthen the banking sector and make it more resilient by developing new capital requirements that provide banks with sufficient capital for future crises and different risk types (Varotto, 2011, BCBS 2023).

Since risks of various types affect the banking industry, the regulations stipulate that banks must have capital set aside for each type of risk to absorb them (Leo et al., 2019). The size and risk of a banḱs assets are the most critical factors in determining how much capital the bank must hold for specific risk types. In the literature, a wide range of risk types are discussed. The main types of risks are credit, market, and operational risks. The different risk types vary in intensity, reflected in the risk distribution functions triggered by various factors (Apostolik et al., 2012, Rosenberg and Schuermann, 2006). More recent studies have shown that liquidity risk is another vital aspect banks need to care about as a systematic risk factor (Dang and Nguyen, 2020). Additionally, regulatory and strategic risks are listed in the literature, as well as many more types like reputational risk (Leo et al., 2019, Chockalingam et al., 2018, Aziz and Dowling, 2019).

#### 2.1.1. Risk types

It is essential to look closely at the individual risk types mentioned to identify the potential for using machine learning in a banḱs risk management. This exercise is necessary to reveal the exact focus areas and application domains.

Credit risk, also called credit default risk, can be defined as the possibility that a borrower or the counterparty will not meet its liabilities according to the agreed terms. This risk is the most significant risk of most banks and arises when either credits or bonds disbursed by the bank are either partially or fully not repaid (Apostolik et al., 2012). Banks review loan applications, require securities, diversify risk, and analyze credit risk to reduce the inherent risk. This analysis is used to evaluate the risk posed by the borrower to determine the interest rate that will be charged. This risk depends on the borrowerś behavior, ability, and willingness to repay the loan. Thus, when granting a loan, the borrower's creditworthiness is checked, which depends on their statistical and personal background (Chen, 2023). In the literature, credit risk is traditionally considered the most significant risk, requiring the most capital to be assigned (Leo et al., 2019).

The risk of incurring losses to a bank resulting from movements in market prices due to changes in foreign exchange rates, interest rates, and equity and commodity prices is called market risk (Apostolik et al., 2012). In the Basel III framework, it is described as the risk of losses in the on-balance sheet and off-balance sheet risk positions due to market price fluctuations (BCBS 2023). A bank needs to monitor market risk as it affects sensitive business segments. For example, interest rate changes are crucial as they can lead to a divergence between revenues and assets and the upcoming cost of liabilities. Interest rate changes can also impact financial securities held by banks or influence customer behavior. A similar impact on banks' profitability can be seen in the exchange rates of foreign currencies. When banks trade equities or commodities, these can also be subject to fluctuations that directly affect profitability (Chen, 2023). The most widely used metric to measure market risk is Value at Risk. It uses statistical probability estimates to assess the potential of financial losses, usually of a portfolio of assets or exposures (Horcher, 2005).

Operational risk is defined in the Basel III framework as the risk of loss due to insufficient or incorrect internal processes, people, and systems or due to external events (BCBS 2023). Therefore, this risk covers many events that impact the business. Errors in internal procedures, such as in transactions, regulatory compliance, and human error, contribute to operational risk. In addition, technical system and software errors or data protection breaches are assigned to operational risk. Furthermore, external risks such as regulatory changes, cyber-attacks, or natural disasters are added (Aziz and Dowling, 2019). Operational risk covers legal risks but does not include strategic or reputational risks (Apostolik et al., 2012). Due to the technology-driven age characterized by constant change, operational risks have become increasingly important in recent decades (Milojević and Redzepagic, 2021).

Liquidity risks pose a significant challenge for banks and arise when they cannot execute transactions at reasonable market prices due to asset liquidity (Dang and Nguyen, 2020, Johri et al., 2022). A bank must ensure enough liquidity to meet credit demands and withdrawals from depositors, which is crucial to meeting short-term financial obligations (Swankie and Broby, 2019). The Basel III framework includes two quantitative ratios that measure liquidity risk. The Liquidity Coverage Ratio, which can be seen as a stress test, aims to ensure that a bank holds sufficient assets to meet all ongoing short-term requirements within 30 days. Furthermore, the Net Stable Funding Ratio, designed to promote medium and long-term liquidity funding for banks, must demonstrate sufficiently stable funding sources. It is calculated as the ratio of the available amount of stable funding to the required amount of stable funding. Both ratios should be at least 100 % (BCBS 2023, Swankie and Broby, 2019).

In addition to the main types of risk, there are numerous other essential risks that banks should consider. Reputational risk is the potential loss resulting from a reduction in a bank's reputation in the public domain. This risk is also of great importance, as damage to reputation causes customers to lose confidence in the bank, and possible customer losses may come as a result (Apostolik et al., 2012). Strategic risk includes incorrect or improper implementation of a strategy and a lack of response to changes in the business environment. Regarding strategy risk, the bank's risk profile is generally based on whether the strategy is moving in the right direction, being implemented correctly, and whether the respective objectives are reasonable (Chockalingam et al., 2018). In a related but different category lies the business risk, characterized by the potential financial loss due to the weakening of the competitive position and market changes (Apostolik et al., 2012). Both risk types relate to the profitability and economic direction of the bank, but they have a crucial difference. The distinction is that strategic risk looks at a long-term overarching period with the strategic orientation of the bank. Business risk considers immediate operational business changes and their impact (Chockalingam et al., 2018). Regulatory and legal risks relate to costs arising from changes in the regulatory environment in the form of new laws and banking regulations (Kelliher et al., 2013). This risk, in particular, affects all risk types and is therefore considered individually based on its impact and significance (Aziz and Dowling, 2019). An additional significant risk is the model risk, which measures the incompleteness or incorrectness of used risk management and assessment methods. This risk is crucial for the application area of ML algorithms because the used model might increase the model risk. Aspects like interpretability, data sensitivity, or overfitting of ML models can impact the model risk (Aziz and Dowling, 2019).

### 2.2. Machine learning principles

Machine learning can be understood as a subset of artificial intelligence that makes it possible for computer systems to learn from data, identify patterns, and predict outcomes without explicitly programming them so that decisions can be made on this basis (Pallathadka et al., 2023). Machine learning can detect meaningful patterns in data and thus extract useful information by learning and adapting. The quality of the predictions strongly depends on the quality and volume of the data (Leo et al., 2019). One possible classification of machine learning models is the division into four types, namely supervised, unsupervised, reinforcement, and ensemble learning. Supervised models use labeled data to train a model and make predictions like classification and regression algorithms. Classification is the process of mapping an input collection of several instances into a unique collection of characteristics, also called targets or labels (Pallathadka et al., 2023). Accordingly, the classifier uses the information of labeled data inputs to classify a new observation by learning the relationships between these inputs. Examples of classification models are Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM), and many more. Unsupervised learning models identify patterns in unlabeled datasets to extract exploratory information and perform actions like grouping similar observations in clusters or storing data patterns. Exemplary unsupervised learning algorithms are k-means clustering, hierarchical clustering, or self-organizing maps (SOM), among others. Reinforcement Learning (RL) algorithms learn by interacting with an environment to maximize a reward or achieve a goal. Therefore, it is a kind of dynamic programming used, for example, in portfolio allocation or trade execution over a specific time horizon (Dixon et al., 2020). Ensemble learning is a technique that combines multiple models to improve predictive performance and enhance accuracy (Kubat, 2017).

The SLR conducted in this study analyzes research papers that have implemented the following steps and actions. To guarantee comparability and, thus, unity, it is essential to outline the implementation process, as critical differences in the research papers will be revealed. Before applying machine learning models to a dataset, it is crucial to prepare the data so the algorithms can process it without problems. This preparation guarantees that qualitative data is made available to the model. This data process is called data preprocessing. Before this begins, it is vital to divide the data set into training, validation, and test data. This is necessary so that the model also works well with new data. Only data that has not been used during training should be tested to evaluate how well the algorithm performs on new data. Adjustments can be made with the validation data set by fine-tuning different parameters before the algorithm is thoroughly tested. The next step is to identify and handle missing values and outliers. In addition, the so-called feature engineering takes place, adding value by creating new variables based on existing ones.

Furthermore, categorical data is encoded into numerical data. Some machine learning algorithms can only process data within a specific range. Therefore, in some cases, the variables must be scaled to the same range. Finally, only variables that add value to the machine learning algorithm, disregarding unimportant variables, are selected in the feature selection step. All these steps are done to ensure the quality of the machine learning algorithm to avoid overfitting and create robustness. A model is overfitting when the algorithm performs well on training data but badly on test data since it learns the irregularities of the training data set, which do not occur in new data sets (Kotsiantis et al., 2006, García et al., 2016).

Due to the reliance on mathematics, probability theory, and statistics, machine learning might produce incorrect classifications (Milana and Ashta, 2021). The performance of machine learning algorithms must be measured to keep track of these errors. This is done with so-called performance metrics or measures. These performance metrics determine the quality of a model based on the correctly and incorrectly classified records. The most common performance metric is the F1 Score. It is the harmonic mean of precision and recall and is suitable for unequal class distributions, as in the case of most machine learning projects (Guerra et al., 2022). In addition, accuracy is another important performance metric for machine learning models. The following formulas from Dixon et al. (2022) show how each metric is calculated. The associated meanings are described in Table 2.1.

$$Precision = \frac{TP}{TP + FP},\ Recall = \frac{TP}{TP + FN},\ F1\ Score = \frac{2*Precission*\ Recall}{Precision + Recall},$$

$$Accuracy = \frac{TP + TN}{All\ Samples}$$

The integration of ML into banking risk management represents a paradigm shift from traditional methods to more adaptive and predictive frameworks. This transformation enables banks to better anticipate and mitigate potential threats, leveraging advanced algorithms for data analysis and pattern recognition. The broad implications of this shift include improved accuracy in risk prediction, enhanced decision-making capabilities, and a more robust approach to managing diverse risk types.

#### 2.2.1. Models

Several machine learning models are already being applied in today's risk management, and new models and approaches are being investigated in scientific research. In the following, the core principles of the most essential algorithms in finance are further analyzed.

Supervised Learning Algorithms

Support Vector Machines are widely used in finance for classification tasks like analyzing stock markets (Rundo et al., 2019). The SVM algorithm aims to find a hyperplane that correctly classifies the input data while maximizing the distance between the different classes. Since an SVM is also a supervised classification algorithm, mathematical optimizations must first be performed on a labeled training data set. Support vectors are the training examples that determine the maximum margin of the SVM. The margin is the distance between these support vectors. SVMs are especially effective in handling high-dimensional data and nonlinear relationships (Cortes and Vapnik, 1995). By adjusting various parameters, the dimension of the input training data can be changed, and thus, the optimal hyperplane can be found. Therefore, overfitting can be avoided since the margin of the support vectors is maximized. Since an SVM has a finite number of controlling parameters, convergence can be reached faster, unlike other machine learning algorithms. As the financial industry deals with many highly complex data and nonlinear trends, SVMs are suitable for overcoming inconsistent and unpredictable performance on noisy data and reliably learning and recognizing patterns (Rundo et al., 2019).

A Decision Tree is a highly interpretable machine learning algorithm that splits the dataset based on the values of features in a recursive manner as an objective to maximize the reparation of the target variable. At each tree node, a decision is made, which forms leaves that produce the final prediction (Kubat, 2017). Since Decision Trees sometimes derive complex and deep tree structures from the input data, they tend to overfit. That is why Random Forests (RFs) were developed. RFs are Decision Tree-based classifiers that average the results of many trees, thus improving the predictive accuracy and decreasing the outcome's interpretability, resulting in a black box (Breiman, 2001). RFs offer high accuracy and robustness, making them useful for complex classification tasks in the financial domain González-Carrasco et al., (2019). One of the common machine learning algorithms in the financial sector is the Logistic Regression model used for binary classification tasks. The model determines the probability that an input belongs to a specific category. A logistic transformation function is applied to a feature set, which maps them into a range of probabilities between 0 and 1, whereby 1 equals 100 percent probability of belonging to the corresponding class. The maximum likelihood function, which maximizes the prediction similarity to the actual outcome, is applied to find the best parameters to train and fit the model to the input data (Hosmer et al., 2013).

Artificial Neural Networks are models inspired by the functioning of a human brain. A neural network typically consists of several layers, where information from the external environment is inserted into the input layer. This information is processed in hidden layers and returned to an output layer. The structure of an ANN is displayed in Fig. 2.1. Each such layer consists of multiple neurons that receive, process, and pass on data. When a neuron receives an input, a weighted sum is applied to that input and adds a bias term. This sum is then passed through an activation function that produces the output. Learning algorithms such as backpropagation and optimization techniques like gradient descent are applied to learn from the data and minimize loss functions by updating weights (Milana and Ashta, 2021). This architecture makes it possible to recognize complex structures and relationships of variables, including nonlinear relationships. A common example of a typical feedforward network is the Multi-Layer Perceptron (MLP), where information flows from input to output in one direction through at least one hidden layer. In Recurrent Neural Networks (RNN), data flows in both directions and sequential information about a hidden state is stored, preserving past information. Popular types of RNNs are long short-term memory (LSTM) and gated recurrent unit (GRU) neural networks. LSTM models have memory cells that retain information for long durations, enabling the evaluation of hidden non-linear correlations and capturing long-range dependencies (Rundo et al., 2019). A GRU is more simplified than the LSTM, as it combines the memory and forget cells, resulting in a leaner architecture that is computationally less expensive (Dutta et al., 2020). Another ANN is the Convolutional Neural Network (CNN). This type can automatically adapt and learn spatial hierarchies of features from the input data. A CNN is particularly effective for tasks that have a grid-like structure because it can extract local translation-invariant features from images, time-series data, or spatial data.

Additionally, they can learn spatial hierarchies for data with complex hierarchical patterns like images (Mashrur et al., 2020). A neural network with many hidden layers is defined as a deep learning model and is even better suited for complex tasks. However, neural networks are considered black-box models, as the increasing complexity with multiple layers makes it difficult to interpret the decision-making and functioning (Giudici et al., 2023).

Bayesian methods are statistical techniques for clustering, classification tasks, and general probabilistic modeling. By updating probabilities based on prior knowledge and new findings, Bayesian methods enable the estimation of unknown quantities and the creation of predictions. A popular algorithm in the financial sector is the Naïve Bayes Classifier. It calculates the likelihood that a data point belongs to a particular class using Bayes' theorem based on the features. The algorithm assumes that the individual features are independent, simplifying the calculations but making the algorithm 'naïve' (Berrar, 2018). Another important Bayesian method is the Bayesian Network. It represents relationships of variables using a directed graph and conditional probability distributions. These distributions show how one variable might influence another one. So, it tells the likelihood of each variable to be in a particular state based on the states of the other variables. This makes it possible for complex reasoning under uncertainty (Lowd and

**Table 2.1**
Confusion matrix.

| | Predicted | |
|---|---|---|
| **Actual** | **1** | **0** |
| **1** | True Positive (TP) | False Positive (FP) |
| **0** | False Negative (FN) | True Negative (TN) |

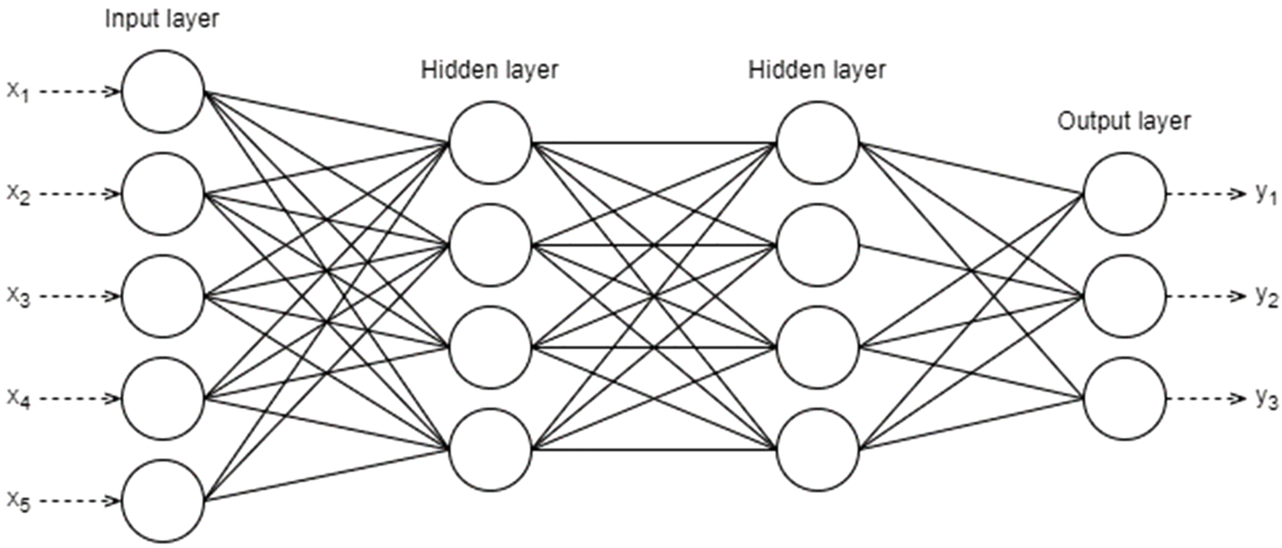


**Fig. 2.1.** Artificial Neural Network structure from Dixon et al., (2020).

Domingos, 2005).

Unsupervised Learning Algorithms

The K-Means clustering algorithm is a model of unsupervised learning that attempts to group data into K distinct clusters so that the sum of squares within a cluster is minimal. It tries to find local optima, which are states where moving a data point to another cluster does not cause a decrease in the sum of squares of the cluster. It starts with a certain number of K clusters and a random selection of K starting points, called centroids. Each data point is added to the nearest starting point, forming the first clusters. Cluster centers are then determined and set as the next centroids. This is repeated until the centroids do not change or a specified iteration count is reached (Hartigan and Wong, 1979). Principal Component Analysis (PCA) is a technique from multivariate statistics. It is strictly not a machine learning algorithm but is often used in conjunction with other machine learning models in Finance and is thus considered essential for this work (Bhatore et al., 2020). The PCA aims to extract the most crucial information from the dataset by reducing the dimensionality. The algorithm identifies those variables with the most tremendous variance as principal components as a linear combination of the original data. These principal components can explain most of the variance in the original dataset. The following principal components are calculated with the condition that they are orthogonal to the first ones and have the largest possible inertia. By projecting the original data onto this coordinate system, unimportant dimensions can be eliminated, and the dataset can be simplified (Abdi and Williams, 2010).

Reinforcement Learning

Reinforcement learning is a category of ML in which an agent interacts with an environment to make a sequence of decisions given the environmental states. The critical difference from classical machine learning methods lies in the type of feedback provided. While in supervised learning, an exact output is given, in an RL model, the agent receives partial feedback in the form of rewards. These rewards encourage the desired behavior without explicitly telling the agent what action to perform. A Markov decision process is commonly used to formalize the problem space. The agent makes decisions based on the current state. These decisions are guided by a policy that updates the probabilities for choosing each action depending on the current state. This can be important in the financial sector, where the market is not fully observable or is high dimensional (Dixon et al., 2020, Singh et al., 2022). RL includes different types of algorithms. Value-based methods indirectly search for the optimal policy, representing the expected return for certain actions in specific states. This category includes algorithms such as Q-Learning, SARSA, or DEEP Q-Network. Policy-based methods aim to optimize the policy that specifies the agent's behavior without a value function. These methods work with stochastic policies that define probability distributions over a set of possible actions. REINFORCE and Actor-Critic Methods are algorithms that belong to this category. Model-based methods are based on an explicit internal model of the environment. This is used to simulate future states and rewards to make better decisions. Model-based methods may be more efficient on a sampling basis but require more computing power. Monte Carlo Tree Search or dynamic programming can be categorized as model-based methods (Dixon et al., 2020, Gašperov et al., 2021). Model-free methods, on the other hand, do not rely on a model of the environment. They learn to make decisions directly from interactions with the environment. This is done to simplify the implementation and to improve scalability. An example of model-free methods is Deep Q-Networks, which extend the Q-Learning with deep neural networks to handle high-dimensional state spaces (Dixon et al., 2020).

Ensemble Methods

Ensemble methods combine multiple individual models to create more robust and accurate predictions than individual models. Bootstrap aggregation, or bagging, is a method in which n subsets of the training data are formed, and a base model is applied to each subset. The subsets are formed by bootstrapping. If a training record has already occurred in a subset, it has the same chance to be included in the subsequent subsets. The individual results of the n subsets are aggregated and combined. Bagging achieves good results with low error rates of single classifiers because these errors can be corrected by the other classifiers (Kubat, 2017). Boosting is a set of methods in which the models are trained sequentially, with each model attempting to correct the errors of the previous model. The outcomes of the models are weighted and then aggregated to make a final prediction. Misclassified instances are weighted higher and are therefore rated as more important for the next instance (Kubat, 2017).

### 2.3. Study relevance

The integration of structured and unstructured data, coupled with the exponential growth in data volume, has made machine learning an essential component of decision-making processes in the financial sector. Traditional methods often cannot handle the variety of data types that characterize modern finance (Bhatore et al., 2020). The algorithms described can meet the growing demands by predicting market fluctuations, making data-driven decisions, or identifying unusual activity. This is particularly advantageous for risk management in banks, as the algorithms may help determine and treat the identified risk types. However, machine learning is not universally superior to traditional methods in every aspect of risk management. For example, some algorithms' black-box problems, in other words, the inability to interpret the decision-making process, can be a significant disadvantage. Especially for risk management, which is subject to many regulations, this aspect can become a problem, as decisions must be made comprehensibly (Giudici et al., 2023). Accordingly, an analysis of the usage of ML for the different risk types is of significant use for banks to identify potentials, problems, and limitations. Comparable analyses have already been carried out in academic work. However, these studies do not include the most recent research results and focus mainly on credit risk (Leo et al., 2019, Shi et al., 2022). The other types of risk are also crucial to banks as they affect the financial stability and the bank's operating business. Understanding and managing these risks provides an approach to ensure a bank's resilience under different circumstances.

## 3. Methodology

The application of machine learning in banking risk management is extensively documented in the literature. Many research papers deal with different algorithms and analyze their suitability for different scenarios that can be subordinated to the risk types. Considering the large amount of work and various methodological approaches in the domain, a systematic literature review is the most appropriate method to summarize the results in terms of the research objectives. A SLR is particularly useful for capturing the complexity and heterogeneity of financial risk management, identifying research gaps, and providing a structured foundation for future research efforts. Likewise, the principles and benefits of SLRs that Kitchenham (2004) points out, such as providing a framework for new research activities and analyzing the actual impacts of the research, are more valid reasons for choosing this research method (Kitchenham, 2004). A suitable framework for conducting the SLR is provided by the PRISMA 2020 statement, which offers an updated guideline for reporting systematic reviews (Page et al., 2021). Following the proposed guideline, the process is recorded in detail to ensure a thorough and transparent documentation of the review process, which is crucial for the reproducibility and understanding of the steps and decisions performed.

### 3.1. Search process

A search strategy is developed for this systematic literature review to identify the relevant literature. This strategy was adapted to two scientific databases: Web of Science and IEEE Xplore. Numerous databases were analyzed for the quality of their entries, and these two databases provide the best and most differentiated results. They cover the most important journals and conferences according to which the literature was filtered. The search process was performed for journal articles, conference proceedings, and review articles from 2013 onwards for the last ten years. This time limitation was undertaken to analyze only the latest research findings. A first analysis of existing literature showed that relevant research in the context of this study increased significantly from 2013 onwards. From this year onwards significant advancements in computational power, the expansion of large data sets and the development of new ML algorithms led to a rapid increase in the adoption of ML techniques in different areas, including risk management in banking. As a result, numerous studies have been carried out in the last few years. Accordingly, the latest research findings are analyzed, and the most recent advancements and trends are captured. Scientific work published until November 2023 is included in the analysis.

The search starts with identifying relevant keywords and search strings aligning with the research objectives. It should be mentioned that the syntax of the search strings and the input options vary in the scientific databases. A general search string is given for simplification, which must be adapted for the respective databases. The search string starts with the banking-related keywords since machine learning algorithms should be analyzed for the banking risk management sector. This is followed by keywords related to the identified risk types, excluding credit risk. Finally, keywords are added to the search string for machine learning and specific algorithms. A detailed presentation of the searched topics with the corresponding keywords and connecting operators is shown in Table 3.1. The keywords and the resulting structure of the search string were identified via the initial review of the literature. The fundamentals chapter and related systematic literature reviews on similar topics were the basis for the search string (Bhatore et al., 2020, Kitchenham et al., 2009). Some acronyms are omitted from the search string as they were used for other keywords. For example, in this context, the acronym RF of Random Forest stands for "Regulatory Framework" or "Risk-Free Rate," and the DT of Decision Tree stands for "Digital Transformation." The search is performed on all fields and is not limited to abstract, title, and keywords, as a comparison showed that important literature was excluded with a corresponding filter.

### 3.2. Eligibility criteria

The literature determined by the search string is filtered by criteria defined here to be used for the analysis. The literature is picked for analysis if it is in the subject area of computer science, artificial intelligence, finance, economics, or other business and additional mathematical-related fields. This excludes areas such as environmental and engineering sciences or other non-relevant categories. The respective areas can be automatically filtered on the Web of Science or manually analyzed by the title, abstract, and keywords on IEEE Xplore. A study is included if it discusses a relevant topic regarding this study's objective. This involves a manual quality assessment by analyzing the title, abstract, and conclusion.

Furthermore, an article or paper is excluded if it is not accessible or not published in English. The review does not include studies that have merely referred to machine learning or artificial intelligence in banking risk management. The studies must either have tested and validated individual algorithms for corresponding use cases or deal with the exact application possibilities and potentials for the different risk types. Only studies with defined research objectives and a degree of experimental rigor and thoroughness are included in the review to ensure further quality. The workflow of selecting studies is displayed in Fig. 3.1. The records tracking is illustrated in Fig. 3.2, which shows that many studies were excluded during the review process. This is initially because the large search string identifies a wide range of literature, which is necessary to ensure no information is omitted. As only a few filters, such as the data and subject area filter, are used, many results are included at the beginning. A breakdown of the search results using more filters would

**Table 3.1**
Search string.

| Topic | Operator | Keywords |
|---|---|---|
| Banking | AND | ("Banking" OR "Bank") |
| Risk Management | AND | ("Risk Management" OR "Market Risk" OR "Operational Risk" OR "Liquidity Risk" OR "Market Volatility" OR "Model Risk" OR "Business Risk" OR "Strategic Risk" OR "Reputational Risk" OR "Security Risk" OR "Cyber Security") |
| Credit Risk | NOT | ("Credit Risk") |
| Machine Learning | AND | ("Machine Learning" OR "ML" OR "Artificial Intelligence" OR "AI" OR "Algorithm" OR "Deep Learning" OR "DL" OR "Reinforcement Learning" OR "RL" OR "Supervised" OR "Unsupervised" OR "Ensemble Learning" OR "Support Vector Machine" OR "SVM" OR "Decision Tree" OR "Random Forest" OR "Logistic Regression" OR "Neural Network" OR "ANN" OR "Naive Bayes" OR "Bayesian Network" OR "K-Means" OR "Principal Component Analysis" OR "PCA" OR "Boosting" OR "Bagging" OR "Classification" OR "Clustering" OR "Regression") |

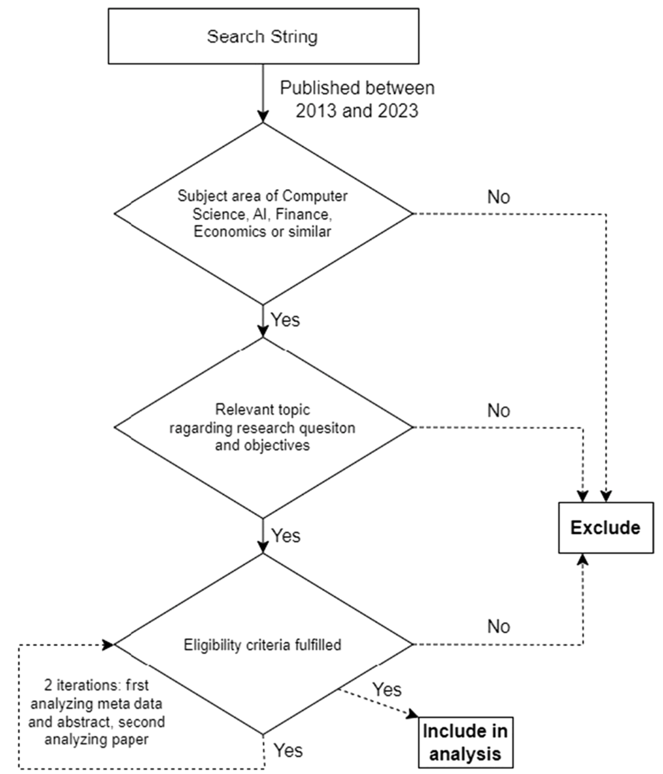


**Fig. 3.1.** Workflow of selecting studies (Shi et al., 2022).

have been possible. However, additional filters and further breakdowns during test runs revealed that relevant studies were excluded. Hence, a large proportion of the results from the first phase are retained. The following manual assessment of titles, abstracts, and keywords leads to a further reduction of records. Numerous papers with topics irrelevant to the SLR's objective are excluded. The specialization of this topic ultimately leads to a significant reduction of the records considered in the review.

## 4. Results

### 4.1. Quantitative analysis

Looking at Table 4.1, the focus of the studies is on the analysis of market and operational risks. Based on the identified study topics that deal with market risk, a trend can be derived for predicting various situations, such as market fluctuations or rates. The prevalence of studies focusing on market risk underlines the importance and complexity of this aspect of risk banks face. As dealing with market risk often requires accurate forecasting of different scenarios, the properties of machine learning algorithms seem to fit well, and therefore, extensive research is crucial. In addition, many studies deal with operational risk, which examines weaknesses in internal processes and systems (Aziz and Dowling, 2019). It can be observed that sometimes, this risk is associated with regulatory and reputational risk. This connection to other types of banks comes as they are interconnected. When internal processes like fraud detection are disrupted or fail, it can damage the reputation or affect compliance with regulations (Qasaimeh et al., 2022). The topics of machine learning in operational risk are very diverse, as they bring value to many areas like cybersecurity, fraud detection, and customer-related issues. In comparison, liquidity risk, as well as other types, are analyzed less intensively.

As seen in Fig. 4.1 more studies have been published in recent years. The figure shows the publication fluctuations, with a notable increase observed in the last several years from 2019 onwards. The initial small number of studies published indicates that the application of machine learning to banking risk management was not a research focus, and the recent increase in publications included in this study reflects the growing interest in leveraging ML in the banking domain.

Furthermore, Fig. 4.2 shows the number of algorithms used, whereby it can be seen that methods based on ANN predominate. In addition, SVM and RF are also often used for risk management-related issues.

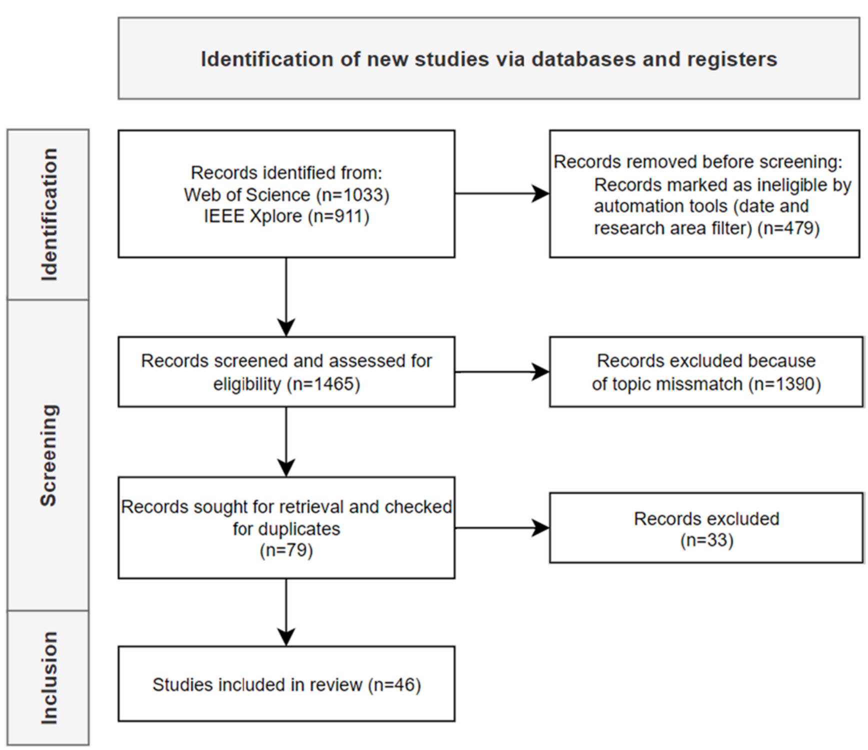


**Fig. 3.2.** Tracking of records based on Prisma Flow diagram (Page et al., 2021).

**Table 4.1**
Systematic literature review results.

| Risk Type | Topic | Algorithm | Reference |
|---|---|---|---|
| Market Risk | Cryptocurrency | RNN | (Dutta et al., 2020) |
| Market Risk | Portfolio Management | ANN, RL | (Gu et al., 2021) |
| Market Risk | Stock Market Prediction | ANN | (Alamsyah & Zahir, 2018) |
| Market Risk | Stock Market Prediction | Regression Algorithms | (Sarangi et al., 2023) |
| Market Risk | Stock Market Prediction | ANN, CART, Bagging ensemble learning | (Hua et al., 2022) |
| Market Risk | Portfolio Management | DL | (Lin et al., 2021) |
| Market Risk | Portfolio Management | RL, DL | (Ngo et al., 2023) |
| Market Risk | Financial Risk Prediction | ANN, PCA | (Liang, 2017) |
| Market Risk | Market Indicator Prediction | SVM, ANN, DL | (Cheevirot et al., 2023) |
| Market Risk | Stock Market Prediction | RNN, ANN; XGBoost | (W. Chen et al., 2023) |
| Market Risk | Market Indicator Prediction | Genetic Algorithm, RNN | (Tan, 2019) |
| Market Risk | Cryptocurrency | RL | (Shahbazi & Byun, 2022) |
| Market Risk | Market Indicator Prediction | ANN | (Stege et al., 2017) |
| Market Risk | Performance Prediction | ANN | (Balci & Ogul, 2021) |
| Market Risk | Performance Prediction | ANN | (Wanke et al., 2016) |
| Market Risk | Financial Risk Prediction | CNN | (Taylor & Keselj, 2021) |
| Market Risk | Market Indicator Prediction | DL | (Daniali et al., 2021) |
| Market Risk | Cryptocurrency | RNN | (Freeda et al., 2021) |
| Market Risk | Stock Market Prediction | RNN, CNN, XGBoost | (Tengxi, 2023) |
| Market Risk | Stock Market Prediction | RNN | (Chatterjee et al., 2022) |
| Market Risk | Stock Market Prediction | ANN | (Wang et al., 2019) |
| Market Risk | Performance Prediction | RF, Linear Regression, DT, PCA | (González-Rossano et al., 2023) |
| Operational Risk | Cybersecurity | ANN | (Qasaimeh et al., 2022) |
| Operational Risk | Fraud Detection | KNN, SVM RF, Stochastic Gradient Descent | (Tadesse, 2022) |
| Operational Risk | Customer Relationship | Outlier Detection, K-Means | (Ullah et al., 2019) |
| Operational Risk | Customer Relationship | Logistic Regression, RF, SVM, KNN, DL | (Seid & Woldeyohannis, 2022) |
| Operational Risk | Fraud Detection | Deep RL | (El Bouchti et al., 2017) |
| Operational Risk, Regulatory Risk, Reputational Risk | Money Laundering Detection | ANN | (Yu et al., 2022) |
| Operational Risk | Operational Risk Measurement | Fuzzy CNN | (Pena et al., 2021) |
| Operational Risk, Regulatory Risk, Reputational Risk | Fraud Detection | SVM, K-Means | (Viji et al., 2021) |
| Operational Risk, Regulatory Risk, Reputational Risk | Fraud Detection | Logistic Regression, SVM, RF, XGBoost, ANN | (Gangula et al., 2023) |
| Operational Risk | Operational Risk Measurement | ANN | (Taweerojkulsri & Limpiyakorn, 2014) |
| Operational Risk | Cyber Security | Naïve Bayes, RF | (Ajeetha & Madhu, 2019) |
| Operational Risk | Cyber Security | DT, Boosting, KNN, RF, Naïve Bayes | (Sahingoz et al., 2019) |
| Operational Risk | Operational Risk Measurement | Semi-supervised few-shot learning | (Zhou et al., 2021) |
| Operational Risk | Operational Risk Measurement | Bayesian Networks | (Sanford & Moosa, 2015) |
| Operational Risk | Customer Relationship | Logistic Regression, RF, Naïve Bayes, SVM, ANN, DT, KNN | (Shetu et al., 2021) |
| Operational Risk | Cybersecurity | SVM | (Masduki et al., 2015) |
| Operational Risk, Regulatory Risk, Reputational Risk | Fraud Detection | K-Means, RF | (Liu et al., 2019) |
| Liquidity Risk | Asset-Liability-Management | DL, PCA | (Krabichler & Techmann, 2023) |
| Liquidity Risk | Liquidity Risk Assessment | ANN, Bayesian Network | (Tavana et al., 2018) |
| Liquidity Risk | Cashflow Prediction | Graph-Based ML, Gradient Boosting | (Kawahara & Takeuchi, 2021) |
| Liquidity Risk | Financial Risk Control | DL | (Xu & Yang, 2022) |
| Liquidity Risk | Liquidity Risk Assessment | Logistic Regression, SVM, Naïve Bayes, RF, XGBoost | (Guerra et al., 2022) |
| Business Risk | Bankruptcy Forecasting | ANN | (Zaychenko & Zgurovsky, 2019) |
| Business Risk | Financial Crisis Prediction | ANN | (Zhailybayevich & Hamada, 2023) |

### 4.2. Qualitative analysis

#### 4.2.1. Market risk

The SLR has identified various application areas and topics for market risk. It can be observed that the most significant subject area deals with the prediction of the stock market. In addition, other topics deal with market-specific problems, such as portfolio management or interest rate and performance predictions. Studies dealing with crypto-currencies were also included in the analysis due to their growing importance for the financial market and banking sector in recent years.

Several studies deal with predicting the stock market (Alamsyah and Zahir, 2018, Sarangi et al., 2023, Hua et al., 2022, Chen et al., 2023). The researchers pursued different approaches. Alamsyah and Zahir (2018) improved the accuracy and the mean squared error for predicting the Indonesian stock exchange composite based on macroeconomic variables using ANN (Alamsyah and Zahir, 2018). In addition, the suitability of various regression algorithms and the application of Classification and Regression Trees in combination with bagging ensemble learning for short-term stock price prediction were also investigated to achieve improved results compared to traditional methods (Sarangi et al., 2023, Hua et al., 2022). Moreover, different types of neural networks were used to predict internet money funds and stock volatility (Tengxi, 2023, Chatterjee et al., 2022). ML algorithms can predict share and market prices and their corresponding risks. In a study on forecasting China's stock market risk, various risks were first identified using VaR. The risks and various fundamental, technical, and

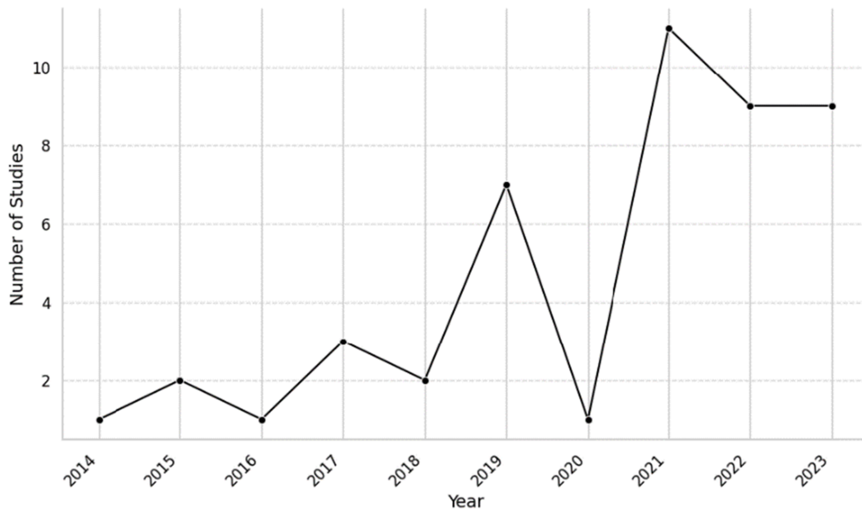


**Fig. 4.1.** Amount of studies published per year.

macroeconomic indicators were used for prediction. Subsequently, several different types of neural networks and boosting algorithms were used for prediction, significantly improving the financial early warning system through enhanced performance metrics (Chen et al., 2023). Since Value at Risk is one of the most used traditional risk measures, its prediction may be helpful for enhanced risk management and informed decision-making. Wang et al. (2019) present a novel ANN-based VaR forecasting method by incorporating external market information to improve the accuracy of the S&P 500 index. The researchers chose this approach since traditional methods are usually based on model assumptions. ML models, on the other hand, can better capture non-linear patterns and complex relationships, which can lead to improved predictions as market dynamics are considered and changes can be adapted (Wang et al., 2019).

Another widely covered area is cryptocurrency. Two studies propose an approach for bitcoin price prediction using Recurrent Neural Networks. Dutta et al. (2020) compared different types of Artificial Neural Networks using the root means squared error. The feature engineering in this study is conducted by considering Bitcoin as an alternative investment that offers diversification benefits and another investment option than traditional methods. Thus, a holistic approach was considered to select the predictor variables. Based on this, an analysis has shown that Recurrent Neural Networks like LSTM and GRU outperform traditional machine learning models with smaller root mean squared error (RMSE). With limited data, these ANNs can effectively regularize past data to learn from non-linear patterns (Dutta et al., 2020). Another study supports these findings by showing that RNNs are more effective for Bitcoin price predictions than other ML algorithms. RNNs have better accuracy than Naïve Bayes, RF, SVM, or K-Nearest-Neighbor (KNN), a simple classification and regression algorithm (Freeda et al., 2021). Shahbazi and Byun (2022) applied RL techniques with an asset allocation method to manage risks within the cryptocurrency framework. RL showed high performance compared to other ML approaches due to its learning-based nature, which increases the accuracy of information delivery (Shahbazi and Byun, 2022).

Machine learning algorithms' ability to analyze historical data, identify patterns, and optimize strategies is particularly beneficial for portfolio management. In the review, three papers that deal with machine learning in portfolio management were identified. In the first study, the researchers analyze the portfolio optimization problem in the digital currency market. The advantages of DL for Feature Expression Learning and Reinforcement Learning in decision-making are combined (Gu et al., 2021). Second, DL is used to manage portfolio risk and maintain investment performance. Lin et al. (2021) propose a DL solution to facilitate the design of risk factors. By employing a neural network, the researchers demonstrate superior performance in explaining stock return variance, improving portfolio volatility, and achieving stability (Lin et al., 2021). Another approach is comparing the

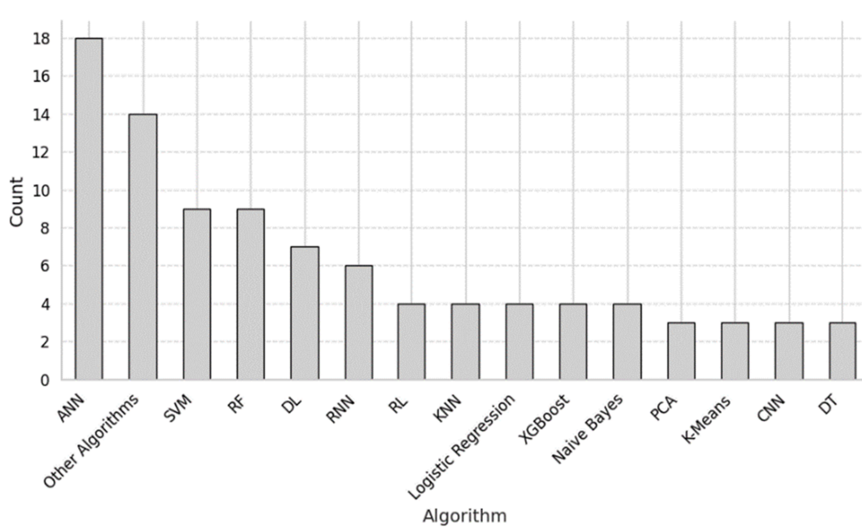


**Fig. 4.2.** Counts of algorithms used in studies.

performance of DL with RL and traditional portfolio optimization models like PCA or Hierarchical Risk Parity in frontier and developed markets. By analyzing sharp ratios and other metrics with different test settings, the researchers show that RL consistently performs better than traditional methods in a typical market environment and an environment with high market volatility. In contrast, DL performs well in a normal condition. However, in a high degree of market fluctuation, traditional and other ML methods perform better due to the sensitivity to data distribution indicated by the market condition (Ngo et al., 2023).

Assessing the resilience to market fluctuations by analyzing banks' performance and profitability is crucial to banking market risk. González-Rossano et al. (2023) analyze the profit income drivers in Mexican banks. Several prediction models were tested using machine learning algorithms like Linear Regression, DT, RF, and PCA. The researchers found that RF can be considered reliable in profit prediction with a lower mean absolute error than the other models (González-Rossano et al., 2023). Another study focused on the performance prediction of Asian banks by utilizing ANN and contextual variables. The variables contain criteria like capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk. Different banks' profitability was compared based on RMSE (Wanke et al., 2016). Balci & Ogul (2021) also employ an ANN for performance measurement by predicting the return on equity of Turkish state deposit money banks (Balci and Ogul, 2021).

Another area in which ML algorithms can be applied is the prediction of market indicators. Tan describes the prediction of the London Inter Banking Offered Rate, one of the most crucial interest rate markets worldwide, using a combination of genetic algorithms and RNN. Genetic algorithms are based on the principles of natural selection and genetics (Tan, 2019). In another study, the projections of mapping interest rates using neural networks in combination with cointegration analysis are investigated. The findings show that combining traditional time series analysis with ANN improves the ability to project interest rates, offering an addition to relevant stress testing in the financial sector (Stege et al., 2017).

Additionally, Daniali et al.'s (2021) research on predicting the volatility index is based on DL and aims to improve accuracy in socially responsible portfolio management, including sustainable investment decisions. The results highlight the improved accuracy of the model in estimating the volatility index, underlining its practicality and potential for promoting sustainable investment strategies (Daniali et al., 2021). Cheevirot et al. (2023) evaluate traditional financial models and ML approaches in predicting foreign exchange market volatility. SVM, ANN, and DL exhibit superior predictive capabilities than the traditional models. The ANN and DL models performed well in providing precise volatility prediction due to their ability to capture intricate relationships (Cheevirot et al., 2023).

A further area of market risk identified in the SLR is the prediction of financial risks in the market environment. Two studies have dealt with different aspects of this topic. An ANN-based approach deals with a financial risk early warning system for China. It is based on PCA, which was used to determine the weights of indicators to integrate the comprehensive financial security index (Liang, 2017). Taylor and Keselj (2021) examine the prediction of financial distress in financial intermediaries by combining traditional financial ratios, sentiment analysis, and additional factors like interest rates in their study. Using a CNN on a dataset of 20 intermediaries over four years, the model achieved an accuracy of 88.24 % in classifying distressed and non-distressed intermediaries (Taylor and Keselj, 2021).

#### 4.2.2. *Operational risk*

During the systematic literature review, numerous areas that deal with operational risk were identified. Researchers address many different subject areas assigned to the operational domain of risk management. These categories are operational risk measurement, cybersecurity, fraud detection, money laundering detection, and customer relationships.

Operational risk measurement is essential to risk management, serving as the cornerstone for comprehensive assessment, quantification, and mitigation of potential threats. The first study dealing with this topic describes the development of a tool that provides predictions of operational risk events, aggregate operational loss distributions, and operational VaR within a central Australian bank. The authors propose a Bayesian Network approach to model smaller, more frequent, attritional operational loss events. As small failures can cause significant operational failures, tools that address these local-level events may have significant impacts. The researchers developed a large model in collaboration with professionals from the Australian banking sector. The model is partitioned into seven categories: (I) skills, experience, and working environment; (II) transaction characteristics; (III) human errors; (IV) error types; (V) payment failure events; (VI) exposure management events; (VII) regulatory/ legal/ tax events. The model aims to generate probabilities of identified operational loss events within structured financial operations. The Bayesian Network model encapsulates the probability-based relationships between the model's risk factors (Sanford and Moosa, 2015). A different method addresses the challenge of operational risk classification by employing a semi-supervised few-shot learning approach called MetaRisk. It aims to enhance classification accuracy in identifying new risk types in the system. As the model learns from labeled and unlabeled data, it is helpful for scenarios with a small amount of data, improving the ability to generalize to new tasks. Because of the limited data availability, the researchers used the few-shot approach, enabling the model to learn from a few labeled examples. This hybrid approach is beneficial for risk management in banks, where obtaining labeled data for different risk scenarios is limited. Compared to other methods like Logistic Regression, Deep Learning, Support Vector Machines, and more, the researcher's MetaRisk model showed better performance metrics like different variations of the F1 Score and accuracy (Zhou et al., 2021).

Besides the classification of operational risk, the assessment of losses also plays a role in risk management. Taweerojkulsri and Limpiyakorn (2014) researched a learning model for assessing loss severity of operational risk using a backpropagation neural network as a predictive model. The focus lies on developing an alternative to expert-based risk assessments, especially in larger banks where operational loss data is available. The model is trained on expert judgments to understand causal chains and effects. The neural network's input layer comprises four categories: actor, threat type, event type, and resource, with further subcategories. With an accuracy of 94.72 %, the model is a solid method for predicting the loss severity of operational risk scenarios (Taweerojkulsri and Limpiyakorn, 2014). A different approach to estimating operational risk capital is proposed by Pena et al. (2021). Their study aims to estimate the operational loss component within a bank by using a fuzzy convolutional deep learning model. In this context, fuzzy logic deals with reasoning that approximates the degree of truth and is not absolute in binary values. The model can integrate internal databases within an organization (observed loss events) and external databases made available by other organizations (available databases of loss events). This ensures compliance with the guidelines of the Basel agreements. The model successfully identified credibility features within the databases to estimate the loss component from multiple sources of risk scenarios, showing its adaptability, stability, and credibility. The model's flexibility makes evaluating risk for new financial products or technological platforms valuable (Pena et al., 2021).

As the banking industry has been characterized by the technological advances of recent decades, computer systems are used in all areas and processes of a bank. These information technology systems must be protected against cyber-attacks to ensure continued operation. Machine learning can also be helpful for cyber security. Qasaimeh et al. (2022) propose advanced security testing using a network-based cyber-attack forecasting model for financial institutions based on deep neural networks. The model is designed to better protect banks from unknown suspicious activities by anticipating the occurrence of cyber-attacks. The model was able to forecast suspicious behavior with 90.36 % accuracy in the validation phase in a real-life banking test environment and thus offers a solid foundation for identifying network-based threats (Qasaimeh et al., 2022). The following studies were not conducted in a direct banking context, but the benefits for banks are illustrated. Therefore, the studies are included in this review. Another possible threat area is distributed denial of service attacks. These attacks involve abnormal network traffic to overwhelm a target server or network, making it inaccessible to legitimate users. Ajeetha and Madhu (2019) used the Naïve Bayes and Random Forest algorithms to detect that type of attack. In the test phase of the two algorithms, the researchers found that Naïve Bayes delivered better results than RF with 90.9 % accuracy (Ajeetha and Madhu, 2019). Another intrusion detection system was proposed by Masduki et al. (2015), who implemented an SVM-based approach with close to 96 % accuracy (Masduki et al., 2015). Due to the rapid growth in Internet use in the banking sector in recent years, an increasing number of phishing attacks are occurring. These attacks are characterized by fraudulent attempts to obtain sensitive information by pretending to be trustworthy sources via emails, websites, or other channels. Sahingoz et al. (2019) propose a real-time anti-phishing system using seven classification algorithms and natural language processing features. Analyzing a dataset of 73,575 Uniform Resource Locators (URL), the Random Forest algorithm, in contrast to the other algorithms, performed best in all performance metrics tested (Sahingoz et al., 2019).

Since fraud is an unsolicited part of today's financial system, several researchers approach this problem with different concepts. First, Tadesse (2022) suggests a fusion of supervised machine learning models and control rules. The study shows that a targeted application of predictive models combined with control rules aids in detecting actual fraud occurrence. Additionally, the researcher emphasizes the crucial role of graph analysis in identifying fraud networks. An RF model performed best with accuracy, precision, and recall scores above 90 %. False alarms have significantly reduced (Tadesse, 2022). Another approach to counter fraud uses a deep RL method. Combining DL techniques with RL principles allows an agent to make sequential decisions in a complex environment. The author only deals with the theory of this approach but presents the benefits of risk management, including identifying patterns in customer data that signal potential fraud and enhancing security in general (El Bouchti et al., 2017). The research of Liu et al. (2019) on detecting suspicious transactions within bank accounts includes a K-means clustering algorithm combined with RF to identify and analyze suspicious transactions effectively. They focus on highly imbalanced data where fraudulent transactions comprise only a tiny part of the data set. By combining these two algorithms, the researchers aim to address the imbalance in data and enhance the accuracy. Combining the algorithms results in improved performance metrics, such as an F1 Score of 92 % (Liu et al., 2019). Viji et al. (2021) present another study dealing with fraud by introducing an intelligent anomaly detection model for automatic teller machine booth surveillance using machine learning. With automatic teller machines, banks face a point of attack for criminal activities, which must be considered by operational risk management. Accordingly, the researchers present an intelligent surveillance system that identifies abnormal activities with the help of SVM. First, video clips from the machines were encoded and clustered using the K-Means algorithm. The results of the SVM were then compared with the RF classifier and showed better predictive performance (Viji et al., 2021). Financial losses can arise from inadequate internal processes or systems.

Banknote authentication is an essential internal process for banks to maintain the integrity of transactions and to prevent counterfeit banknotes leading to financial losses. Gangula et al. (2023) investigate various ML models for banknote authentication. They use a dataset containing variance, skewness, kurtosis, entropy, and class values to distinguish between genuine and forged banknotes from image data. The tested ML models are LR, SVM, RF, Extreme Gradient Boosting (XGBoost), and ANN. While all algorithms performed well, the ANN consistently outperformed the other algorithms with better performance metrics, highlighting its effectiveness in accurately classifying banknotes (Gangula et al., 2023).

Money laundering is a critical threat to banks as it is an unlawful process that hides the origin of illegal money, exposing financial institutions to potentially serious regulatory sanctions or reputational damage (Apostolik et al., 2012). Effectively detecting and thus preventing money laundering is a crucial process for banks, which can be enhanced as well by machine learning. Yu et al. (2022) propose an anti-money laundering risk identification model using a graph-based Convolutional Neural Network using transaction information to identify risky customers. Due to the nature of the data being graph-structured, the neural network learns from its ability to model and learn effectively from the relationships and dependencies of transactions. This approach offers compelling predictions with better accuracy and recall scores than an RF model (Yu et al., 2022).

Analyzing customer relationships is essential for the operational business of a bank as it can be used to identify potential churn or dissatisfaction influencing operational continuity and profitability. Thus, it directly impacts the day-to-day running of banking operations. Transaction volumes or usages of services like customer service will change with varying customer numbers. Churn prediction can help banks to improve internal processes and services or to ensure quality. It can also be of a strategic or business nature, but as there is an impact on daily operations, it is classified as an operational risk. Ullah et al. (2019) used K-means and outlier detection algorithms to predict customer churn and highlight this process's importance for banks (Ullah et al., 2019). Another study analyzing bank customer churn prediction compares ML algorithms like Logistic Regression, RF, SVM, KNN, and DL. For an Ethiopian commercial bank dataset, the DL approach outperformed the other methods with adequate performance metrics (Seid and Woldeyohannis, 2022). A bank's operational business is heavily dependent on its customers. The extent of customer churn is directly linked to customer satisfaction, and thus, it is also characterized as an operational risk. Shetu et al. (2021) predict the satisfaction of an online banking system in Bangladesh using ML. They compare various ML algorithms used on survey-based data, and with accuracy scores of 96 %, KNN, Logistic Regression, and RF achieved the best scores (Shetu et al., 2021).

#### 4.2.3. *Liquidity risk*

The number of studies dealing with liquidity risk is smaller than that of market and operational risk. In addition, very different topics are dealt with, which cannot be summarized in a few categories. One article deals with the potential of Deep Learning in asset-liability management. The researchers state that their approach is computationally less intensive than traditional methods. Additionally, risk appetite can be controlled by choosing appropriate objectives associated with rewards in the learning algorithm. Furthermore, regulatory constraints can be enforced by choosing penalties adequately. Therefore, machine learning provides a robust framework that supports balanced risk-taking and risk-adjusted pricing (Krabichler and Teichmann, 2023).

The assessment of liquidity risk is another area considered by the identified studies. Guerra et al. (2022) investigate if ML algorithms can model liquidity risk and provide insights for stress-testing scenarios. They classify credit institutions from Portugal regarding their liquidity risk using actual data from 2014 until 2021. Then, a comparison of various ML algorithms to a traditional statistical model as a benchmark is conducted. The comparison included Logistic Regression, SVM, Naïve Bayes, RF, and XGBoost classifiers. As a result, the other ML techniques outperform the traditional Logistic Regression approach, with good precision and F1 Scores. The XGBoost classifier mainly results in good performance metrics, indicating a suitable solution as a decision support or early warning system for liquidity risk modeling (Guerra et al., 2022).

Tavana et al. (2018) analyze the usage of ANN and Bayesian Networks for liquidity risk assessment. As the banking environment is constantly exposed to changes, a neural network is particularly capable of predicting liquidity risk metrics like the LCR because of its learning features. The two models were applied to a dataset from a U.S. bank over eight years. The ANN was structured with one hidden layer to approximate the liquidity risk function. In the second phase, a Bayesian Network identified influential indicators affecting the liquidity risk, like liquidity and loan/deposit ratios. Then, the fitted Bayesian Network was compared with the risk function developed by the ANN, showing that the BN approximates the risk function with high precision. Thus, the Bayesian Network confirmed the ANN trend, demonstrating the appropriateness of both models for measuring liquidity risk (Tavana et al., 2018).

Cash flow prediction is a crucial aspect of liquidity risk as it enables anticipating liquidity shortfalls and managing the working capital effectively. Kawahara and Takeuchi (2021) used a graph-based ML approach for this task to improve the predictive capabilities. The prediction model is DT-based combined with a gradient boosting method, enabling time series prediction and incorporating non-linear relationships (Kawahara and Takeuchi, 2021).

Financial risk control is crucial for liquidity risk management as it identifies and treats potential threats to safe banks' liquidity. Xu and Yang (2022) focus on assessing banks' liquidity risks using deep neural networks. The researchers measure and predict liquidity risks from static and dynamic perspectives and propose suggestions for the financial risk control of commercial banks. In this case, static measurements include assessing liquidity at a specific point in time, whereas dynamic measurement analyzes over a period, considering changes and trends in a bank's financial condition. The predictions are performed using an ANN of the analytic hierarchy process, which connects subjective and objective assessment methods. This approach combines the strengths of a decision-making framework that helps to prioritize and analyze multiple criteria or goals with the predictive capabilities of an ANN. The authors compared it with other ML models to verify the effectiveness of their model, resulting in better performance measures (Xu and Yang, 2022).

#### 4.2.4. *Other risk types*

The SLR identified numerous studies that deal with market, operational, and liquidity risks. The analyzed studies also deal with other risks but to a smaller extent. Two studies have dealt with topics that can be subordinated to business risk (Zaychenko and Zgurovsky, 2019, Zhailybayevich and Hamada, 2023). Zaychenko and Zgurovsky (2019) propose a method for Ukrainian banks' bankruptcy forecasting. It addresses the importance of predicting bankruptcy risk, which is related to the instability or even potential failure of banks, characterizing business risk. The researchers tested different fuzzy neural networks and compared them to traditional financial risk assessment methods. The study highlights the superior predictive accuracy of fuzzy neural networks over traditional methods (Zaychenko and Zgurovsky, 2019). A further investigation into the use of ANN in this domain describes developing a predictive model for financial crises in banks. The researchers emphasize the importance of tailored predictive models for banks depending on the circumstances and suggest using various prediction algorithms to enhance early warning systems (Zhailybayevich and Hamada, 2023). Both studies aim to predict bankruptcy in banks. Thus, they are considered a business risk due to their direct impact on financial stability, investors' trust, and other effects on the business environment.

The studies do not directly cover other types of risk. Studies only cover regulatory risks indirectly that deal with money laundering and some aspects of fraud detection (Liu et al., 2019, Viji et al., 2021, Gangula et al., 2023, Yu et al., 2022). In the realm of banks, adapting to and complying with changes in the regulatory environment is crucial to mitigate possible negative consequences (Kelliher et al., 2013). Accordingly, the studies' findings can help reduce regulatory risk. In addition, this has further-reaching consequences on reputational risk. If banks do not counteract violations of money laundering and fraud regulations, this negatively affects customer trust and the bank's reputation.

## 5. Discussion

### 5.1. *Literature synthesis*

As stated in the introduction, this review aims to understand how and in which areas of risk management banks can use ML algorithms to deal with market, operational, liquidity, and other risks. As a generalization, it can be said that ML techniques can benefit all areas of risk management. The advantages of ML have already been extensively demonstrated, especially in the management of credit risks (Bhatore et al., 2020, Chen et al., 2017, Shi et al., 2022). However, other risk types can benefit from ML as well. The utilization and effects of various algorithms were analyzed in detail for the market risk in the literature. The predictive capabilities of ML algorithms are used for the prognosis of stock markets, cryptocurrencies, banking performance, market indicators, and financial risk, as well as for portfolio management. The recent increase in publications compared to previous years shown in Fig. 4.1 is due to technological advances, increasing industry adoption, and changing requirements in banking. These aspects drive increased interest in applying ML methods to address various risk-related issues. This shift underlines the increasing recognition of the potential of utilizing ML in banking risk management.

The utilization of ANN and their different variations from DL to RNN or CNN is particularly significant. In most studies, researchers use elements of these models to deal with the many use cases. ANN's suitability for treating market risks can be attributed to several causes. ANN can recognize complex data patterns and relationships. This is particularly useful for the market risk domain, as the markets of numerous industries and sectors are linked to the banking sector. Therefore, market risk involves many variables like interest rate, currency, and price fluctuations, which must be considered to generate reliable models. ANNs enable diverse data inputs by incorporating different network configurations by parameter tuning to adapt to different market environments. Since ANNs can handle non-linear high-dimensional data, they are suitable for mapping the complex interrelationships of the financial markets (Dixon et al., 2020). As a result, ANN-based models can provide better performance metrics than traditional approaches to address market-specific problems (Freeda et al., 2021, Cheevirot et al., 2023). RL is another algorithm that is often used for market risk. It can be used well for this risk type as it can overcome market-related issues by continuously adapting strategies to the changing market environment. As RL can interact with an environment, it can learn from market feedback and iteratively tune decision-making processes to handle dynamic market scenarios and manage volatility (Dixon et al., 2020). This adaptability makes RL valuable for optimizing risk strategies customized to the dynamic character of market risks.

Further algorithms, such as ensemble methods or regression algorithms, are widely used, highlighting their usefulness in dealing with specific market risk challenges. Depending on the use case, corresponding ML algorithms can make predictions, optimize portfolios, or handle diverse risks in the market landscape. These strengths are reflected in the number of studies identified to support risk management in an evolving market environment.

ML is also proving to be a promising approach for banks in operational risk. The SLR shows the various applications of ML in areas ranging from operational risk measurement to cybersecurity, fraud detection, money laundering prevention, and customer relationship analysis. The effectiveness of various algorithms is demonstrated by robust performance metrics, underlining the value of operational risk management. These models show potential for improving risk identification, classification, and mitigation strategies. The broad range of algorithms shows different performances in overcoming specific problems. In contrast to market risk, no algorithm can be identified as universally applicable. This is due to the complex nature of the operational risk domain, which addresses a range of tasks in internal processes and systems, fraud detection, or the analysis of customer relationships. Each area is diverse and requires specific methods, so a single algorithm cannot universally solve all operational risk problems. However, RF, SVM, and ANN were analyzed quite extensively. The properties of RF allow to deal with outliers and noise in the data and show good accuracy (Breiman, 2001). RFs help deal with different data types, feature sets, and high-dimensional data (Liu et al., 2019, Shetu et al., 2021).

Additionally, RFs perform well in settings with imbalanced labels and provide insights into the importance of features, thus being valuable for fraud detection or cyber-attack prediction (Breiman, 2001). As SVM can handle linear and non-linear relationships, they can be used for various scenarios, especially showing good performance in classification tasks in cybersecurity, fraud detection, or customer churn prediction (Masduki et al., 2015, Viji et al., 2021, Seid and Woldeyohannis, 2022). As ANNs are suitable for pattern recognition tasks, they can detect potential threats like irregularities in data and continuously learn and adapt, enhancing the ability to detect anomalies and irregularities. In operational risk management, these features are perfect for dealing with unusual behavior in network traffic, fraud, money laundering, or assessing loss severity (Qasaimeh et al., 2022, Taweerojkulsri and Limpiyakorn, 2014, Gangula et al., 2023, Yu et al., 2022). Despite their predictive solid performance, some algorithms like ANN or RF have a black-box nature, resulting in a lack of interpretability, which is a problem for the highly regulated banking industry (Giudici et al., 2023).

Compared to the other risk types, research on liquidity risk in the context of ML has been less extensive. The main reason for this is the lack of qualitative and available data. Banks rarely provide internal liquidity data, which leads to less research on this risk type. Nevertheless, essential areas of liquidity risk are highlighted. For example, the potential of DL for asset liability management and the advantages of risk-adjusted pricing are emphasized (Krabichler and Teichmann, 2023). Another focus is comparing the liquidity risk for stress test analyses of traditional methods and boosting algorithms or Bayesian methods. The ML methods are more appropriate, indicating their suitability as a support system (Guerra et al., 2022, Tavana et al., 2018). ML is also used to forecast cash flow and control financial risks, making it an effective instrument for managing liquidity risks. Despite the limited number of published studies, the SLR demonstrates the benefits of ML for liquidity risk. The ability to make predictions and risk assessments is crucial for liquidity risk. No algorithm emerges as dominant for individual tasks. The algorithms stand out in different areas due to their inherent strengths.

The other less significant risk types are even less studied. Some studies indirectly cover only business, regulatory, and reputational risks. ANNs are used for the business risk domain to forecast bankruptcy and financial crises (Zaychenko and Zgurovsky, 2019, Zhailybayevich and Hamada, 2023). As business risk focuses on risks threatening the competitive position and operations, these studies can be subordinated to business and not to market risk (Apostolik et al., 2012). Both studies utilize ANNs due to their predictive and learning abilities. Some studies that deal with operational risk also focus on regulatory and reputational risks. This is because a failure in fraud detection and money laundering might have significant consequences, as regulations stipulate. Breaking these regulations can seriously affect a bank's reputation (Aziz and Dowling, 2019). Different algorithms are selected in the studies depending on the use case.

In a nutshell, the systematic literature review reveals significant trends in the application of ML across different risk types. For instance, artificial neural networks (ANNs) and support vector machines (SVMs) are prominently used for market risk prediction, demonstrating their ability to capture complex, non-linear relationships in financial data. In operational risk, ML algorithms are crucial for fraud detection and cybersecurity, showcasing their versatility and robustness in identifying and mitigating diverse threats

### 5.2. Practical implications

This research contributes to improving banks' risk management by exploring and analyzing the application of ML techniques across various risk types. By performing the SLR, the existing studies that leverage ML addressing different aspects of risk within banks have been synthesized. This synthetization of insights provides an overview of current practices, strengths, and limitations in employing ML algorithms in risk management. The SLR contributes to practitioners' understanding of the current maturity of utilizing ML. It is shown that incorporating ML techniques into risk management strategies allows banks to analyze large datasets with varying data types. This leads to enhanced risk assessment, identification of threats, and decision-making.

Furthermore, ML enables improved market trends, operational deficiencies, and liquidity shortage prediction. This helps to analyze risk proactively and develop mitigation strategies. Moreover, the SLR highlights the utility of different algorithms in dealing with specific challenges. This is useful for selecting and implementing the most appropriate algorithms for particular needs. The algorithms can be adapted to the risk types by adjusting various parameters to fine-tune risk treatment.

Additionally, resources can be better allocated as more data is collected in banks because of technological change. Due to the large amounts of data, numerous areas can be analyzed, and thus, banks can focus more quickly on areas in need. Strategical decision support also benefits from ML. The derived insights help to make strategic decisions by better understanding risk patterns, market behavior, and customer relationships. This is additionally beneficial to develop new dynamic strategies to adapt to evolving risks. Collected customer data can be used to build predictive customer analyses that offer insights to build customer-centric products and services. Fundamentally, integrating ML algorithms into banking risk management enhances the robustness and the ability to adjust strategic positioning to different risk types to respond to threats in a dynamic environment.

Indeed, the advancements in ML contribute to the overall stability and reliability of the banking sector. By enabling more accurate risk assessments and proactive threat mitigation, ML helps banks maintain operational continuity and safeguard against financial losses. These improvements not only enhance the financial health of individual institutions but also contribute to the stability of the broader financial system.

Also, some practical implications are in order. On the one hand, Banks can strategically integrate ML into their risk management frameworks to enhance their predictive capabilities and operational efficiency. This integration requires addressing challenges such as data quality, model interpretability, and regulatory compliance. By adopting a strategic approach, banks can leverage ML to gain a competitive edge in risk management. On the other hand, ML's ability to provide more transparent and accurate risk assessments can help banks meet stringent regulatory requirements. Regulators can also benefit from ML's insights to better understand the risk landscape and develop more effective oversight mechanisms.

### 5.3. Limitations

One of the main limitations of this review is the focus on the Web of Science and IEEE Xplore databases. This focus could have excluded relevant studies from journals or conferences published on other databases. A manual comparison of various databases before the SLR showed that the two databases publish the best-fitting studies and include the most important journals and conferences regarding the nature of the research objectives. Thus, further studies may be relevant, but no groundbreaking new findings are expected to be found that have not also been identified by the analyzed databases. The included studies show a mainly positive outcome of employing ML in banking risk management domains. This might indicate a publication bias, skewing the findings towards favorable ML outcomes. Some crucial negative aspects, like the lack of interpretability, are sometimes mentioned but not further investigated (Krabichler and Teichmann, 2023, Jensen and Iosifidis, 2023). Another significant limitation is the sole focus on scientific research. Since this review only analyzed scientific papers from journals and conferences, grey literature is left out. Potentially valuable findings from the banking sector, such as reports or industry papers, have not been considered. Furthermore, this study focuses exclusively on the potential of ML, whereby other technological methods and approaches in risk management were not examined. In addition, the possibility of integrating ML based on readiness and maturity in the banking sector has not been analyzed.

### 5.4. Further research

Further research directions can be derived based on the findings of this review. Initially, it is essential to mention that market risk has been dealt with extensively. However, no studies have been conducted that specifically analyze market risk in the risk management context of banks. The studies deal with topics relevant to market risk and can be transferred but are not in an explicit risk management context. Further research efforts in this area would be advisable. An actual analysis of a bank's risk management procedures and processes with subsequent identification of the application potential through case studies and stress testing could offer a possible solution. This proposal is also supported by Leo et al., who call for more studies directly related to risk management (Leo et al., 2019). Since then, research efforts specifically related to operational and liquidity risk in the context of ML have been conducted (Guerra et al., 2022, Sanford and Moosa, 2015, Zhou et al., 2021, Taweerojkulsri and Limpiyakorn, 2014). Additionally, the integration of nowcasting techniques could provide valuable real-time insights into risk management, allowing for more responsive and dynamic decision-making processes (Sadok et al., 2023).

Nevertheless, the scope of the studies analyzing liquidity risk can expand to gain more detailed insights. An analysis of the relationships between individual risk types could be helpful to understand how different categories influence each other. This would allow more in-depth risk management strategies to be drawn up. For instance, integrating sentiment analysis into risk management by analyzing social media data could be beneficial for a comprehensive understanding of market movements and customer-related issues, reputation, or credit risk. An initial analysis of the feasibility of this would provide further insights. Another area that can be further explored is the integration of existing risk management frameworks with machine learning algorithms. Traditional methods have often been compared with ML (Sarangi et al., 2023, Hua et al., 2022, Zaychenko and Zgurovsky, 2019). Integration into existing frameworks would involve examining the challenges and potentials, focusing on adoption challenges, implementation scalability, and institutional barriers. For this purpose, the actual processes and maturity levels must be examined to generate added value with ML.

Additionally, qualitative studies like expert interviews, case studies, or surveys can further analyze institutional barriers like governance or stakeholder engagement. This is useful for measuring the acceptance, maturity level, and deployment potential of ML in a bank's risk management. Explaining decision-making processes or portfolio allocation with ML to different stakeholders is very important (Fritz-Morgenthal et al., 2022). Researching the black-box problem is an elementary component of further research efforts. The integration of ML methods with regulatory requirements and the effect on ethical aspects should be examined. Scientific research has made progress in employing ML in banking risk management. The findings should be linked to the practice, with interdisciplinary cooperation between scientists and industry stakeholders. These efforts can foster innovative approaches by sharing data concepts and findings to integrate the benefits of ML into risk management in a sustainable fashion.

In the same breath, it is important to mention four key topics: emerging risk areas; ethical and responsible AI; scalability and real-time processing; and cross-disciplinary approaches. Significant progress has been made in applying ML to traditional risk areas like credit and market risk. However, emerging risks such as cyber risk, climate risk, and operational resilience require further exploration. Research should investigate how ML can predict and mitigate these emerging risks, considering their unique characteristics and the dynamic nature of the risk landscape.

From another angle, the ethical implications of using ML in banking must be considered. Future research should address issues related to bias in ML models, ensuring these models do not perpetuate existing inequalities or unfairly disadvantage certain groups of customers. Developing frameworks for ethical AI in banking is essential for maintaining public trust and regulatory compliance.

As the volume of financial data continues to grow, scalable ML solutions capable of real-time processing will become increasingly important. Research should focus on developing ML models and architectures that can efficiently handle large-scale data and provide real-time insights. This capability is crucial for applications like fraud detection, where timely intervention is necessary.

Lastly, the complexity of banking risk management requires a cross-disciplinary approach that combines insights from finance, computer science, statistics, and regulatory studies. Future research should promote collaboration across these disciplines to develop more comprehensive and effective ML applications. Such collaboration can lead to innovative solutions that address the multidimensional challenges of modern banking risk management.

## 6. Conclusion

The constantly increasing amount of data accumulated in the financial sector requires continuous analysis to leverage it effectively. Banks' risk management requires the integration of advanced analyses of various data. ML is becoming increasingly common as a suitable option for overcoming the changes and challenges in risk management. This SLR provides an overview of ML learning algorithms used in banks' risk management about market, operational, liquidity, and other risk types. Research into the application of ML has revealed innovative methods and their benefits in the banking sector. The review results highlight the central role that ML algorithms play in the assessment, prediction, and mitigation of the different risk types. The analysis revealed that scientific research focuses on market and operational risks. In particular, the potential of Artificial Neural Networks and other algorithms, such as Support Vector Machines or Random Forests, was researched. The studies have successfully predicted market dynamics, portfolio management, fraud detection, and cyber security. Research in the direct context of a bank's risk management is desirable regarding market risk. In addition, further analysis of ML for liquidity risk is needed to gain more precise insights. The results underline the opportunities for using ML in risk management. It is highlighted that further research is required to unlock the full potential of ML and enable banks to develop their risk mitigation strategies further. Utilizing the potential requires further research so that ML can be integrated into existing frameworks by overcoming institutional barriers. This SLR underlines the central role of ML in redesigning risk management practices. The results provide insights into current practices and highlight areas for further research to exploit the full potential of ML. Leveraging the inherent capabilities of ML for risk management in the banking sector not only meets current challenges but also leads institutions into a data-driven future of resilience and strategic decision-making.

## CRediT authorship contribution statement

**Valentin Lennart Heß:** Writing – review & editing, Writing – original draft, Software, Methodology, Conceptualization. **Bruno Damásio:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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