

Review

Artificial Intelligence and Machine Learning in FinTech: From Predictive Analytics to Optimization Approaches

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Abstract

Artificial intelligence (AI) and machine learning (ML) are increasingly important in financial technology (FinTech) applications involving large datasets, uncertainty, and complex decision-making. First, this paper presents a review of AI- and ML-based approaches in FinTech from 2010 to 2025, with particular emphasis on the relationship between predictive analytics and optimization-based decision-making. The review identifies two major research streams: (i) predictive AI/ML models for financial forecasting, stock price prediction, risk management, and fraud detection and (ii) optimization approaches for constrained financial decision problems, including portfolio optimization, asset–liability management, and risk-based decision-making. These two streams have largely evolved independently, which creates challenges in real financial environments, where uncertainty in predictions directly affects decision quality. Secondly, the paper also provides a decision-oriented perspective on how AI/ML-based predictions can support optimization under uncertainty and practical financial constraints. It highlights the role of uncertainty-aware optimization, simulation-based methods, and hybrid approaches such as simheuristics in improving the robustness of financial decision-making. Finally, the paper identifies open research directions toward integrated financial decision-support frameworks that combine predictive analytics, optimization, and simulation to address dynamic and uncertain FinTech environments.

Keywords: FinTech; machine learning; artificial intelligence; predictive analytics; metaheuristics; optimization; financial decision-making



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1. Introduction

In the modern financial sector, where complex data flows are continuously generated and volatility is increasing, accurate forecasting has become an essential component of strategic decision-making and effective risk management. Financial forecasting refers to the estimation of future financial patterns and behavior using historical data, market information, and other predictive factors. The accuracy of these estimates is critical, as they directly influence investment decisions, financial management, and corporate strategy [1]. As noted by some authors [2], financial data, especially for big data analysis, has become increasingly large-scale, heterogeneous, and unstructured, posing significant challenges for traditional econometric models that depend on clean, structured data with limited volume. Consequently, such data are often high-dimensional, where the number of variables (features)

can exceed the number of observations [3]. In the current dynamic financial environment, enterprises and organizations face increasing complexity in managing financial risks [4]. Globalized markets, the development of new financial instruments, and stricter regulatory requirements have intensified the challenges of risk assessment and decision-making. Traditional financial risk management strategies, which are often based on historical data and qualitative assessments, are insufficient under rapidly changing financial conditions. Predictive analytics can support decision-making under uncertainty by enabling data-driven financial risk management. This improves the reliability of financial models and the ability of institutions to respond to market uncertainty [5].

For decades, financial analysis has relied on classical statistical techniques to identify patterns in data. In this context, artificial intelligence and, in particular, machine learning provide new opportunities by enabling the modeling of complex, nonlinear, and high-dimensional financial relationships. ML is closely associated with big data, which refers to datasets characterized by large volume, high dimensionality, or both [6]. From a technical perspective, ML can be viewed as a core subset of AI focused on learning from data. In contrast, AI systems may also include broader capabilities beyond learning, such as reasoning and autonomous decision-making. Some authors describe full AI systems as those capable of automating data identification, testing, and decision-making based on data-driven evidence [7]. The financial sector generates a continuously growing volume of data, including transactional records and market indicators. This data-rich environment provides a suitable setting for AI applications, particularly for developing predictive and analytical models [8]. AI-based systems can assist financial institutions in handling complex and uncertain market conditions by identifying patterns in historical and real-time data [9]. Within this context, ML enables systems to detect patterns and derive insights from data without explicit programming. This adaptability supports a wide range of financial forecasting and decision-support applications [10]. Moreover, regulatory pressures and evolving customer expectations are pushing financial institutions to adopt intelligent systems that are both transparent and compliant. With the development of cloud infrastructure and edge computing, low-latency data processing enables real-time decision support, allowing AI models to be integrated directly into financial workflows [11]. These developments are not limited to large multinational banks.

Several managerial problems in finance and insurance can be formulated as combinatorial optimization problems. Traditionally, exact methods have been used to obtain optimal solutions. One well-known example is the classical Markowitz model [12], which minimizes portfolio risk subject to a minimum return constraint. However, exact methods face limitations when applied to large-scale optimization problems with realistic constraints, many of which are NP-hard. In such cases, solutions are often limited by simplifying assumptions or high computational cost [13]. In contemporary financial applications, advances in operations research and computer science have introduced new solution approaches. Exact methods based on mathematical and constraint programming techniques are now often complemented by approximate algorithms, such as heuristics and metaheuristics, to obtain near-optimal solutions for complex combinatorial optimization problems [14]. The rapid dynamics and increasing internationalization of financial markets have made decision-making more complex, while stricter regulation has imposed additional constraints. This has increased the need for methods capable of modeling and solving complex optimization problems in banks, central banks, institutional investors, and insurance companies [13]. Metaheuristics are widely recognized as effective solvers for combinatorial optimization problems, including hard optimization cases [15]. A metaheuristic is a high-level heuristic framework designed to solve a broad class of problems without requiring major modifications to its structure. These methods iteratively improve candidate solutions using

general search strategies. Their main strength lies in their flexibility and ability to produce good-quality solutions across diverse problem structures [16]. Still, several challenges remain in the rapid integration of AI into FinTech. Ethical concerns, particularly algorithmic bias and data privacy, are critical issues that must be addressed to ensure responsible deployment [17]. Balancing innovation with ethical and regulatory requirements is therefore essential for sustainable development in the financial sector. Given the diversity of AI, statistical learning, optimization methods, and financial applications, a systematic classification is needed to structure the literature. Based on this survey, studies are grouped into two main categories according to the role of data-driven methods (Figure 1): predictive analytics and optimization-based decision-making (prescriptive analytics). Predictive analytics focuses on identifying patterns in historical data to support forecasting tasks, while optimization-based decision-making focuses on identifying optimal financial strategies under constraints.

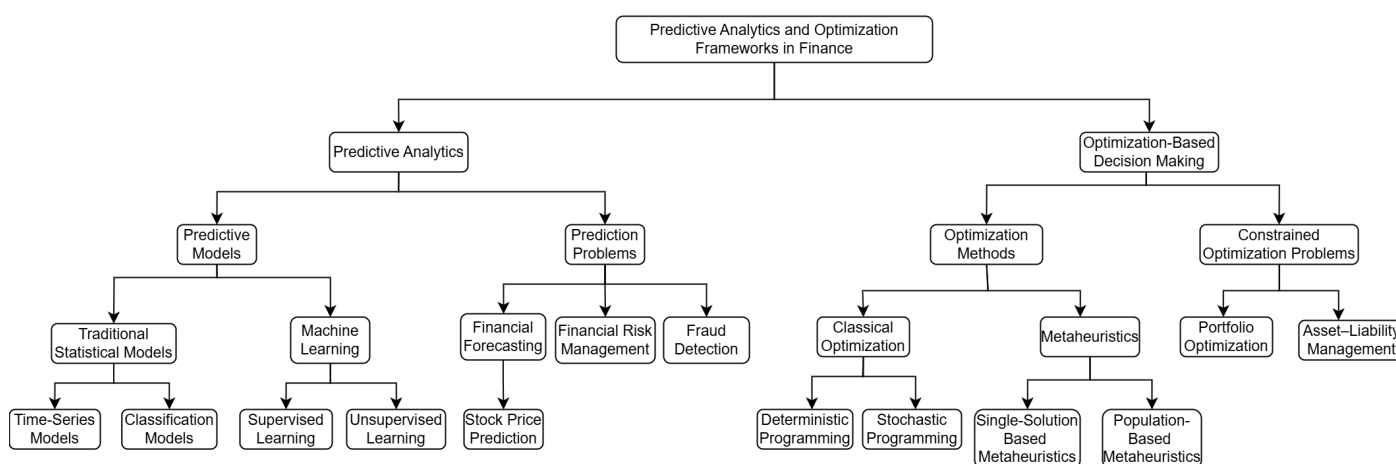


Figure 1. Classification of predictive analytics and optimization-based decision-making frameworks in financial applications.

In this paper, the following research questions are considered: (i) what are the critical applications of AI and ML in predictive analytics for the FinTech and financial services sectors, and what have been the most common methodological trends reported in the literature?; (ii) how have optimization-based approaches, including metaheuristic and simheuristic methods, been applied to financial decision-making problems in FinTech?; and (iii) how can predictive AI/ML models be integrated into optimization-based decision-making systems in financial applications in the presence of uncertainty? The paper analyzes the literature on predictive AI/ML methods and optimization-based decision-making approaches within a unified FinTech framework. It examines both streams of research (predictive analytics and optimization) jointly and highlights their complementary roles in financial and FinTech applications. Moreover, it highlights opportunities for their integration and discusses how hybrid approaches can enhance financial decision-making. The remaining of the paper is organized as follows. Section 2 describes the review strategy used to collect and analyze the relevant literature. Section 3 provides an overview of traditional econometric models applied in financial prediction. Section 4 examines ML approaches for predictive analytics in FinTech applications. Section 5 discusses the use of metaheuristic and simheuristic methods for optimization-based financial decision-making. Section 6 discusses the research gaps and future directions, while Section 7 concludes the paper.

2. Review Strategy

The Scopus database was used to conduct the literature review, covering the period between 2010 and 2025. The search strategy was designed to identify two main streams of research in FinTech: (i) articles focusing on the application of AI and ML in financial domains and (ii) articles applying metaheuristic optimization methods to financial decision-making problems.

Structured Scopus search queries were used to improve the transparency and the reproducibility. For the first stream (application of AI/ML in the financial domain), the search query was TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "support vector machine*" OR "random forest*" OR "gradient boosting" OR "reinforcement learning") AND (fintech OR finance OR "financial services" OR banking OR "financial markets")), and the query for the second stream (metaheuristics and optimization methods) was TITLE-ABS-KEY((metaheuristic* OR "genetic algorithm*" OR "particle swarm optimization" OR "ant colony optimization" OR "simulated annealing" OR "tabu search" OR "differential evolution" OR "evolutionary algorithm*") AND (fintech OR finance OR "financial services" OR banking OR "financial markets")). The initial Scopus search retrieved 32,324 records concerning the AI and ML applications and 2790 records related to optimization and metaheuristic approaches. The records comprised journal articles, conference papers, review articles and book chapters. After the preliminary search, the literature was manually screened by scanning titles, abstracts and assessing the themes of the articles in relation to the objectives of this review. We screened approximately 500 papers by their title and abstract and then by their full text to identify relevant studies. The inclusion criteria were: (i) studies published between 2010 and 2025; (ii) publications in English; (iii) journal articles, conference papers, review papers, and relevant book chapters; and (iv) studies that were directly related to AI/ML applications or optimization and/or metaheuristic methods in financial and FinTech areas. The following were considered for exclusion: (i) non-financial or non-FinTech studies; (ii) insufficient methodological or conceptual relevance of publications to the goals of this review; (iii) duplication of records in the screening process; and (iv) any non-English publications. Additional relevant published studies were identified by using the Google Scholar database and reference tracking from selected published studies.

The manual screening process uncovered duplicate records which were removed. After the screening and eligibility process, 142 studies were retained for detailed analysis and synthesis. These final references were chosen for their relevance, methodological contribution, and their ability to support the comparative analysis of predictive AI/ML methods and optimization-based approaches in the realm of FinTech. A summary of the literature selection and screening process used in this review is provided in Figure 2.

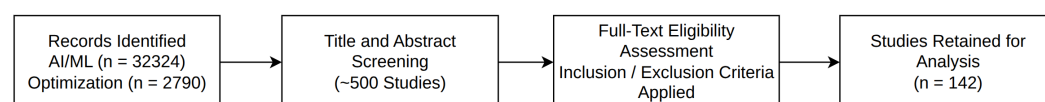


Figure 2. Literature selection and screening process adopted in this review.

To provide an overview of the evolution of the two research streams, the number of publications per year was retrieved from the Scopus search results using the search queries listed above. The records were grouped by publication year and the trends of AI/ML-based studies are presented together with the optimization-based studies from 2010 to 2025 in Figure 3.

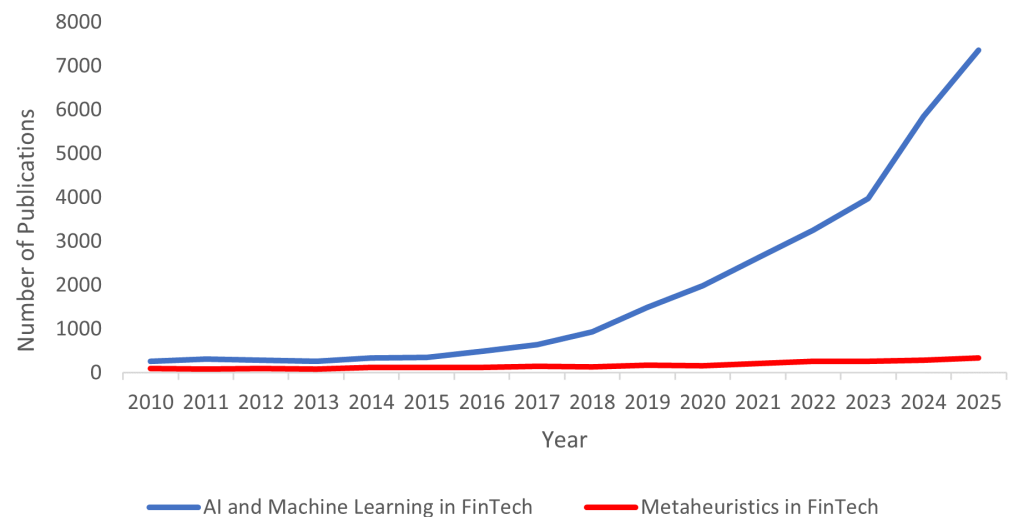


Figure 3. Annual publication trends of AI/ML and metaheuristic-based research in FinTech (2010–2025).

In the early period (2010–2015), publications related to AI/ML showed a steady increase from a relatively higher initial baseline, while metaheuristic-based studies remained scarce and relatively stable. From around 2016 onward, AI/ML research expanded significantly, with a particularly sharp increase after 2018, reflecting the growing adoption of ML methods in predictive financial applications. The number of studies based on metaheuristic approaches also increased over time, but at a slower rate. Publication trends indicate uneven growth in the literature on the FinTech sector, with optimization-based research lagging behind the use of predictive AI/ML methods.

3. Traditional Approaches to Financial Prediction

Finance is a broad term that refers to activities in financial markets, including portfolio allocation and time-dependent investment decisions. These activities typically generate time series data, which can be used to forecast future values and returns [18]. A key assumption in statistical inference from time series data is weak stationarity in the mean, variance, and covariance structures [19]. Econometric and statistical methods have traditionally been used to model financial relationships and to support forecasting tasks. However, with the emergence of big data and high-dimensional financial datasets, many classical statistical methods have become less effective, which has increased the relevance of ML techniques in financial forecasting [20]. In addition to univariate volatility models, multivariate extensions of classical market risk models have been developed using System-GARCH frameworks to capture inter-dependencies between market and interest-rate risks across financial institutions. However, these models require joint estimation of a large number of parameters and rely on strong distributional assumptions, which can limit their practical applicability in high-dimensional settings. Still, ARCH/GARCH-type models continue to be widely used for volatility forecasting in global financial markets [21,22]. Beyond time-series forecasting, traditional statistical methods have also been extensively applied to classification problems in finance. Logistic regression and discriminant analysis are commonly used in credit scoring models [23]. Similarly, fraud detection in financial and electronic transaction systems has often relied on logistic regression models to identify patterns associated with fraudulent behavior based on transaction and user-level features [24].

Traditional econometric models are generally based on assumptions such as stationarity and linearity, which are not always satisfied in real-world financial markets, where

dynamics are often nonlinear and structural relationships may change over time [25]. In addition, these models can struggle with large-scale and high-dimensional datasets, which motivates the use of more flexible and data-driven approaches to improve predictive performance [26]. Table 1 provides an overview of representative econometric models and their applications in financial forecasting and risk analysis.

Table 1. Summary of representative traditional econometric models and their financial applications.

Financial Application	Objective	Traditional Statistical Models	Article
Financial Forecasting	Forecast inflation volatility dynamics	ARCH	[27]
	Forecast market volatility	Hybrid ARMA–GARCH	[22]
	Forecast stock prices	Hybrid ARIMA-based Model	[28]
Financial Risk Management	Estimate Value-at-Risk	GARCH	[29]
	Model market and interest-rate risk	GARCH	[30]
	Predict corporate default risk	Logistic Regression	[31]
Fraud Detection	Identify fraudulent financial transactions	Logistic Regression	[24]

Empirical evidence on traditional econometric risk models suggests that their forecasting performance is highly sensitive to changes in market conditions and that their distributional and stationarity assumptions are often violated during periods of market stress [32].

4. Machine Learning for Predictive Analytics

Financial markets generate large volumes of data on a daily basis. This data provides both opportunities and challenges: it enables data-driven decision-making while also requiring efficient methods for processing and analyzing large-scale datasets. ML algorithms are well suited for this setting, as they can identify patterns in data and improve predictive performance over time without being explicitly programmed [33]. ML methods are commonly categorized into three main types based on the learning paradigm: supervised, unsupervised, and RL. Supervised learning relies on labeled datasets, where input-output pairs (x, y) are provided during training. The target variable y is used to guide the optimization of model parameters through iterative updates [34]. These models are widely used in classification and regression tasks, where the goal is to predict discrete or continuous outcomes from historical financial data. Such approaches are extensively applied in financial predictive analytics and are often embedded in decision-support systems to improve forecasting performance and support data-driven decision-making [5].

Unsupervised learning, in contrast, identifies patterns in data without labeled outputs. It includes clustering, association analysis, and dimensionality reduction. These methods aim to capture the underlying structure of the data and can also be used to detect anomalies as observations that deviate significantly from learned patterns [35]. In finance, unsupervised techniques are commonly applied in anomaly detection, fraud detection, and customer segmentation, particularly when labeled data are limited and patterns must be inferred directly from the data. RL is a learning paradigm in which an agent interacts with

an environment to learn optimal behavioral strategies. The objective is to learn a policy that maps states to actions in order to maximize cumulative expected reward. Rewards may be assigned at intermediate and final steps, providing feedback on the effectiveness of actions with respect to long-term objectives [36].

In predictive FinTech applications, supervised learning methods dominate empirical studies due to the availability of labeled financial data. They are widely used in stock price prediction, credit risk assessment, and fraud detection. Unsupervised methods are less frequently applied and are mainly used for clustering and anomaly detection tasks [37,38]. More generally, ML can be defined as a computational approach that improves performance on a task or generates predictions based on past data [34]. These methods typically rely on the optimization of a loss or reward function. ML models capture complex relationships in data by minimizing prediction error or maximizing performance criteria, leading to flexible representations of underlying data structures [38].

The ML approach to data analysis differs fundamentally from traditional statistical modeling and hypothesis testing. Classical inference tools such as R^2 , t -values, p -values, and statistical significance are less central, while greater emphasis is placed on out-of-sample prediction and the bias-variance trade-off. Regularization techniques are commonly used to control model complexity and improve generalization [39]. Thus, the choice of ML methods in predictive FinTech applications depends on the data structure and the nature of the prediction task. This empirical, loss-based perspective aligns with recent FinTech literature, which treats predictive analytics as a data-driven forecasting problem in noisy and non-stationary environments, where model performance is primarily evaluated using out-of-sample accuracy rather than structural interpretability [40]. Model evaluation is a relevant component of predictive ML, as it determines the generalization ability and accuracy of learned models. Common error-based evaluation metrics in financial forecasting include mean absolute percentage error, mean squared error (MSE), mean absolute error, and root mean squared error, which are widely used in empirical studies [41,42]. Figure 4 displays a taxonomy of the most recurrent predictive analytics applications identified in the literature review. These applications can be classified into three broad categories: financial forecasting, financial risk management and fraud detection. The taxonomy shows the use of AI and ML techniques in different contexts of financial decision making and reveals the wide spectrum of predictive analytics applications discussed in this review.

4.1. Machine Learning for Financial Forecasting

Financial forecasting refers to the use of historical time-series data to predict future values of financial variables such as asset prices, volatility, and returns. Forecasting asset values in financial markets remains one of the most challenging problems in quantitative finance [37]. The growth in computing power and data availability has encouraged researchers and practitioners to adopt methods from data science, AI, and ML. Recent studies suggest that ML algorithms can achieve strong predictive performance in financial forecasting and, in some cases, outperform traditional regression-based methods [43]. Financial forecasting is commonly formulated as a time-series prediction problem in which the objective is to learn the relationship between historical observations and future values of financial variables. Future values depend on past observations as well as additional explanatory variables. A single-step forecasting model can be expressed as:

$$\hat{y}_{t+1} = f(y_{t-k:t}, x_{t-k:t}) \quad (1)$$

where $y_{t-k:t}$ represents the historical values of the target variable over a window of size k , $x_{t-k:t}$ denotes the corresponding input features (e.g., technical indicators or macroeconomic variables), and $f(\cdot)$ is a predictive function implemented using an ML model. Financial

time-series data are often characterized by substantial noise and a low signal-to-noise ratio, making accurate forecasting difficult [44]. In this context, support vector regression (SVR) has been extensively used in financial time-series forecasting as a nonlinear learning approach that is able to cope with noisy and non-stationary data [45], while ML-based forecasting also faces challenges such as data leakage, overfitting, and changing market conditions, all of which can reduce predictive performance in real-world settings. However, these issues can be mitigated through appropriate validation procedures, regularization techniques, and periodic model retraining using updated market data.

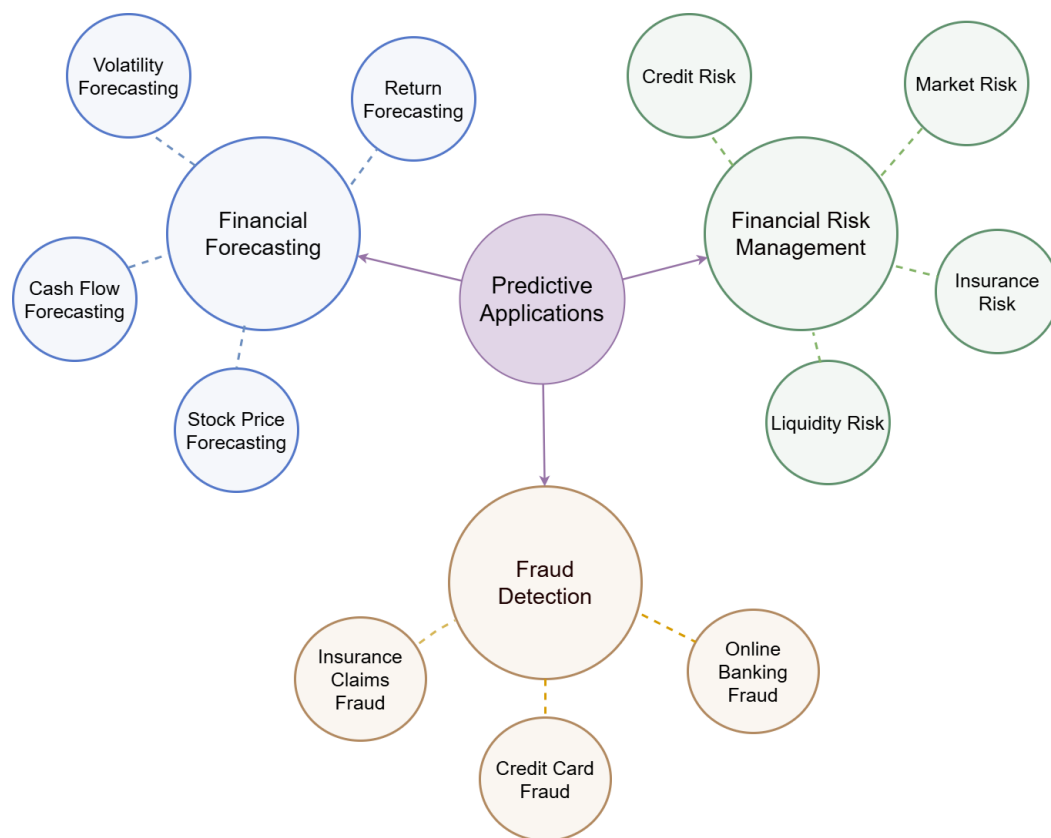


Figure 4. Taxonomy of ML-based predictive analytics applications in FinTech.

Forecasting approaches can generally be categorized into linear and nonlinear models, each offering different capabilities for capturing patterns in financial data [46]. A comparative study by Luong [47] found that ML methods such as Random Forest (RF) and XGBoost are effective at modeling nonlinear relationships in financial time series, whereas traditional approaches such as ARIMA and GARCH remain useful for capturing linear dependencies and volatility clustering. Within this context, deep learning (DL) models have attracted increasing attention because of their ability to learn complex nonlinear and sequential patterns from data. Neural network architectures have been widely applied to financial forecasting tasks, particularly volatility prediction, where temporal dependencies play an important role. For example, some authors have proposed a hybrid forecasting framework that combines a long short-term memory (LSTM) network with GARCH-type volatility models and reported improved forecasting performance [48]. Similarly, recurrent neural network architectures such as LSTM have shown promising results in applications including exchange-rate forecasting [49]. LSTM networks incorporate memory mechanisms that enable them to retain information from previous time steps and capture long-term dependencies in financial sequences [46]. Despite the strong predictive performance reported for ML and DL models, challenges related to interpretability, robustness, and deployment

in real-world financial environments remain significant [50]. Various ML models have been applied to study financial forecasting applications, such as support vector machines (SVM), RF, XGBoost, neural networks, and LSTM. These techniques can be used to forecast volatility, bond returns, cash flows, and insurance claims [43,45,47].

Machine Learning for Stock Price Prediction

Stock price prediction is one of the most extensively studied problems in financial forecasting, as accurate forecasts of future stock price movements can support trading strategies and investment decisions [51]. Numerous studies have applied ML algorithms to analyze historical financial data and complementary information sources, such as economic indicators, to support investment decision-making. Some authors employed ML algorithms to predict stock market movements using historical market data [52], while others forecasted the stock prices of construction companies in Taiwan using a nonlinear prediction model [53]. Stock market prediction is widely recognized as a challenging task due to the inherent uncertainty, volatility, and non-stationarity of financial markets. From an ML perspective, stock prediction is formulated as a data-driven learning problem in which the objective is to model the relationship between past market information and future price behavior. Depending on the formulation, the task may focus on predicting either the direction of future price movements or the future price itself [54]. Accordingly, stock prediction problems can be broadly classified into two categories: directional prediction and price prediction. Directional prediction is typically formulated as a binary classification problem, where the objective is to predict whether the stock price will increase or decrease over the next period [55]. This can be represented as:

$$\hat{y}_{t+1} \in \{0, 1\} \quad (2)$$

where $\hat{y}_{t+1}$ denotes the predicted direction of the price movement. This formulation is particularly relevant for trading strategies in which the direction of return is more important than the magnitude of the price change. In contrast, price prediction is commonly formulated as a regression problem, where the goal is to estimate the future value of a stock price. Regression models learn a functional relationship between historical observations, explanatory variables, and future prices by minimizing a prediction error measure, typically the MSE [56]. This can be expressed as:

$$\hat{y}_{t+1} = f(X_t) \quad (3)$$

where X_t represents the available information at time t , including historical prices and other explanatory variables, and $\hat{y}_{t+1}$ is the predicted future stock price.

ML algorithms enable the analysis of complex and heterogeneous datasets, making them well suited for stock market prediction [57]. A wide range of methods has been investigated, including RF models [58] and SVM [59]. In most studies, stock prediction is formulated as a supervised learning problem aimed at forecasting short-term price changes or directional movements rather than long-term price levels. Some authors examined the impact of different input parameters on artificial neural network (ANN) models for stock market prediction and observed that most ML approaches rely primarily on technical indicators rather than fundamental variables [60]. Other authors investigated deep learning networks for stock market forecasting and highlighted their ability to automatically extract relevant features from large datasets without extensive manual feature engineering [61]. Similarly, other studies applied ANN models using technical indicators derived from historical market data and showed that these models can effectively capture nonlinear patterns in financial time-series data [62]. Other studies also employed technical indicators

as ANN inputs for predicting stock market index movements and reported that neural networks are capable of modeling nonlinear market behavior [63]. Despite these advances, stock price prediction remains a challenging research area due to noisy financial data, changing market conditions, and the difficulty of achieving robust out-of-sample predictive performance in real-world environments [64]. The reviewed stock price prediction studies show that different ML models, such as SVM, RF, ANN, and DL-based models, are applied to both directional prediction and stock price forecasting problems. The results show that technical indicators and historical price information are used as main inputs in many studies, and DL can automatically extract features from large financial data sets. The analyzed studies show that the use of ML can offer valuable tools for modeling the nonlinear and complex behavior of the stock market in general [52,55].

4.2. Machine Learning for Financial Risk Management

ML techniques provide data-driven approaches for modeling complex financial risk patterns and improving predictive accuracy compared to traditional statistical methods. These methods are widely applied in financial risk management, including credit risk, market risk, and regulatory risk assessment. In particular, ML has shown strong performance in credit risk modeling [65]. Within credit risk management, some authors propose an ML approach based on decision trees and SVM, which, when evaluated on real lending data, leads to cost savings of up to 25% [66]. Similarly, other authors show that a multivariate outlier detection method improves credit risk estimation for SME lending using data from UniCredit Bank [67]. Accurate estimation of the probability of default provides more informative risk assessment than a simple binary classification of borrowers as creditworthy or non-creditworthy. Traditional credit scoring methods include discriminant analysis, logistic regression, Bayesian classifiers, nearest neighbor methods, and classification trees. Comparative studies indicate that ML models, including ANN, often achieve competitive or superior performance relative to these classical approaches in credit scoring tasks [68].

In the field of banking risk management, ML has received considerable attention in both academia and industry to better identify, measure, and monitor banking risks, such as credit, market, and liquidity risks, given the ongoing rising complexity in the financial sector [69]. Cluster analysis has proven useful in this context [70], while deep learning models have also been applied to related market risk problems [71]. ML techniques are also used by regulatory authorities such as the U.S. Securities and Exchange Commission in risk assessment processes to detect potential misconduct. These techniques play a role in the monitoring of systemic risk and financial stability [72] while supporting financial institutions in detecting fraudulent and non-compliant transactions via continuous auditing and anomaly detection mechanisms [73].

In the insurance sector, ML methods are widely used to support decision-making by analyzing large and heterogeneous datasets. These techniques enable improved classification and prediction of customer behavior, thereby enhancing actuarial and risk assessment processes [74]. In addition, customer segmentation is often performed using clustering methods such as k-means, which group customers based on similar characteristics and behavioral patterns. These data-driven approaches support more targeted analysis and decision-making, and can improve risk evaluation and product recommendation in insurance systems [75]. The literature shows that ML contributes to financial risk management across credit, market, regulatory, and insurance domains through improved risk estimation and anomaly detection. However, despite its predictive advantages, ML-based risk models face important challenges related to interpretability, transparency, and explainability, which remain critical for real-world deployment in financial decision-making contexts [69]. ML techniques such as RF, ANN and decision trees are used in various financial risk manage-

ment tasks as shown in studies in financial risk management. These techniques have been used in various applications of financial risk assessment, showing the potential of ML in financial risk assessment and classification. The results presented indicate that applying ML techniques to financial risk assessment and management within financial institutions could be beneficial [65,66,68].

4.3. Machine Learning for Fraud Detection

Financial fraud detection is a complex and data-intensive process that involves identifying suspicious patterns, anomalies, and irregular transactions within large financial datasets [76]. In practice, it is not feasible for humans to monitor and detect all fraudulent cases manually. However, timely detection and prevention of fraud are essential for maintaining and protecting customer trust. As a result, automated fraud detection systems are often used as a first line of defense, flagging potentially illegitimate transactions for further investigation [77]. A key challenge in this context is that fraudulent cases are typically highly underrepresented in datasets, which significantly reduces the performance of standard binary classifiers [78]. This class imbalance makes the learning task particularly difficult for conventional models. ML has significantly improved the ability to detect fraud. For example, some authors study credit card fraud detection using ensemble learning methods such as AdaBoost and majority voting [79]. Their work evaluates several ML models, including naive Bayes, RF, and GB trees, and highlights the effectiveness of ensemble techniques in improving detection performance. In particular, their results indicate that AdaBoost is sensitive to anomalies and outliers, making it suitable for detecting rare fraudulent transactions. In general, AI techniques such as neural networks and anomaly detection methods can analyze customer behavior, detect suspicious activity, and support the development of institutional fraud prevention policies [80].

Traditional fraud detection in the insurance sector relied heavily on manual auditing and inspection processes [81]. However, with the increase in data volume and operational complexity, such approaches have become impractical [82]. In addition, fraudsters continuously adapt their strategies, making it difficult to detect fraudulent behavior using fixed rule-based systems [83]. Ensemble learning methods combine multiple models to improve predictive performance compared to individual learners [84]. These techniques have been widely applied in insurance-related tasks, including claims prediction and fraud detection, demonstrating strong practical effectiveness across different settings [85]. The use of ML in the insurance sector has further expanded with the development of deep learning. For example, convolutional neural networks and recurrent neural networks, including LSTM networks, have been applied to image and sequential data analysis [86]. These models allow insurers to evaluate claims more accurately by processing unstructured data such as vehicle damage images. In addition, natural language processing (NLP) techniques combined with ML models have shown strong performance in extracting information from textual data such as customer communications, policy documents, and claim descriptions [87]. Despite their advantages, ML-based fraud detection systems face several limitations, including severe class imbalance [88], evolving fraud patterns, and limited model interpretability [89], which can affect their robustness and reliability in real-world applications. A primary concern related to ML-based fraud detection is explainability and interpretability. Most traditional machine learning architectures operate in a “black box” manner to an extent, limiting easy interpretation of their decision-making processes by financial analysts and regulatory authorities [90]. As a result, explainable artificial intelligence (XAI) has become a growing focus in the financial sector for enhancing transparency, trust, and accountability in AI-based decision-making and fraud detection processes [91]. XAI enables financial institutions to support decision-making in domains such as fraud detection by identifying

potential biases and ensuring fairness in automated decision-making processes [92]. The application of XAI enhances transparency in decision-making, essential for regulatory compliance and operational efficiency [93]. It is common the use of different ML techniques, including ANN, ensemble learning methods, NLP and anomaly detection algorithms, to detect fraudulent activities in financial systems [76,79,81]. Table 2 summarizes representative ML-based studies across key FinTech application areas.

Table 2. Summary of representative ML methods and their financial applications.

Application	Objective	ML Techniques	Dataset	Article
Financial Forecasting	Forecast market volatility	SVM	Shanghai–Shenzhen 300 high-frequency market dataset	[94]
	Forecast bond returns	Neural Networks, Ensemble Methods	U.S. Treasury yield curve and macroeconomic dataset	[95]
	Forecast cash flow	LSTM	ERP transactional and macroeconomic data	[96]
	Forecast motor insurance claims	SVM, Decision Trees, RF, XGBoost	Motor insurance portfolio dataset (Greece)	[97]
	Predict stock price direction	RF, XGBoost	Historical stock market dataset from multinational listed companies	[98]
	Predict stock price direction	ANN, SVM, RF, Naive Bayes	Indian stock market historical dataset	[99]
	Predict directional change event prices	CNN, LSTM	Forex tick price datasets (GBPUSD, EURUSD, USDCHE, and USDCAD)	[100]
	Predict stock price movement	SVM	Historical stock market data and Twitter sentiment data	[101]
Financial Risk Management	Predict bank liquidity risk	RF, ANN	Tanzanian commercial banks financial dataset	[102]
	Classify financial performance of insurance companies	ANN	Jordanian insurance companies' financial dataset (Amman Stock Exchange)	[103]
	Segment insurance policies for risk profiling	K-Means Clustering	Swedish motorcycle insurance dataset (Wasa portfolio)	[104]
	Classify profitable trading signals for risk management	Decision Trees, ANN	FOREX currency exchange market dataset	[44]
	Predict financial distress risk	Decision Trees, AdaBoost	Publicly listed U.S. restaurant financial dataset	[105]
Fraud Detection	Detect fraudulent credit card transactions	RF, ANN (Ensemble)	European credit card transaction dataset	[106]
	Detect fraudulent online banking transactions	NLP-based Methods	FraudNLP online banking transaction dataset (European bank)	[77]
	Detect healthcare insurance claim	RF, ANN	Healthcare insurance claims dataset	[107]
	Detect fraudulent credit card transactions	AdaBoost	European credit card transaction dataset	[79]
	Detect fraudulent automobile insurance claims	K-Means Clustering	Automobile insurance claims dataset	[108]

The analysed studies indicate that the effectiveness of ML techniques depends on the application domain and the nature of the underlying datasets. High-frequency market

data, macroeconomic data, transactional data, and historical stock data have also been used for financial forecasting and stock price prediction, including SVM, ANN, RF, and LSTM models that capture data patterns. Comparative evidence indicates that there are differences in performance between models and datasets. For instance, RF was observed to outperform ANN, SVM, and naive Bayes for stock price prediction, and RF and XGBoost were observed to be superior for motor insurance claims forecasting [97,99]. In financial risk management, decision-tree-based and neural-network approaches have been adapted to structured financial data, with the advent of Adaboosted decision trees demonstrating improved predictive performance than the classical decision trees in financial distress prediction [103,105]. Ensemble and neural network techniques have shown strong effectiveness in fraud detection for highly imbalanced transaction and insurance claim datasets. In contrast, clustering techniques are useful in discovering hidden fraud patterns and customer segments [106–108].

Table 3 summarizes the distribution of ML techniques across the reviewed studies. It presents the frequency of different models in financial forecasting, stock price prediction, financial risk management, and fraud detection. The table is based on the full set of studies analyzed in this review.

Table 3. Frequency of ML models across financial applications.

ML Models	Financial Forecasting	Stock Price Prediction	Financial Risk Management	Fraud Detection
LSTM	3	4		
ANN	3	6	4	2
SVM/SVR	4	5		
k-nearest neighbors	1	2		
Naive Bayes		1	1	
RF	2	3	2	2
Decision Trees	1		3	
XGBoost/LightGBM	1	1	1	
AdaBoost		1	1	1
Regression Models	2		2	
K-Means			1	2
Transformer				2
generative adversarial network				1
Autoencoder				1
Isolation Forest				1

The results indicate that the choice of ML models varies across application domains. LSTM, ANN, and SVM are widely used in financial forecasting due to their ability to capture nonlinear and temporal dependencies in time-series data. In stock price prediction, similar models are frequently applied, particularly neural network-based approaches, SVM, and RF, for both classification and regression tasks such as price direction and trend prediction. For financial risk management, decision trees, ANN, RF, and regression models are commonly used, particularly for classification problems such as credit risk and financial distress prediction. In fraud detection, clustering and classification methods such as K-Means, RF, ANN are often applied to identify anomalous and fraudulent patterns, especially in credit card transaction and insurance claim datasets.

During the last years, large language models (LLMs) and generative AI have gained considerable attention for financial question answering, sentiment analysis, understanding financial documents, predicting market trends, automated financial reporting, and decision support systems, among other applications. Thus, some authors provide a comprehensive review of financial LLMs, highlighting their growing adoption across a wide range of financial NLP tasks and applications [109]. Finance includes decision-making in a setting of uncertainty. Data achieve financial importance when they support a decision: to lend, trade, hedge, rebalance, authorize, examine, disclose, intervene, or regulate. The growth of AI in finance represents a change in the architecture of financial decision-making. AI systems currently obtain information from both structured and unstructured data, transform noisy observations into detectable signals, produce suggestions, trigger alerts, proactively perform actions, and derive insights from outcomes [110]. Traditional ML techniques usually require training on manually labeled datasets. In contrast, the major advantage of advanced LLMs is the reduction or elimination of labeling costs. The integration of LLMs with automated sentiment analysis techniques is a promising direction to improve the efficiency and reliability of financial sentiment analysis so as to facilitate more informed investment decisions [111].

5. Optimization-Based Decision-Making in FinTech

Although predictive analytics focuses on generating accurate forecasts using ML models, many real-world financial decision-making problems follow a predict-then-optimize paradigm, where predictions are used as inputs to optimization models in order to derive optimal decisions under constraints [112]. Within this framework, optimization plays an increasingly important role in the development of FinTech applications, including pricing and valuation, investment risk assessment (e.g., value at risk), transaction cost analysis, portfolio optimization, cross-market investment strategies, and broader financial risk management. Traditional optimization methods include classical techniques such as linear programming, nonlinear programming, quadratic programming, stochastic programming, and dynamic programming [113]. While these methods are mathematically well established, their applicability is often limited to problems that satisfy strong theoretical assumptions, which can restrict their use in complex real-world financial settings [114]. Many combinatorial optimization problems in finance have historically been modeled using deterministic approaches. However, such models often fail to capture the inherent uncertainty and variability of real-world decision environments. Financial systems are typically characterized by dynamic and stochastic inputs, as well as structural constraints, which can lead deterministic models to produce solutions that are optimal only under simplified assumptions. As a result, their practical performance may be suboptimal when applied in realistic settings [115]. To address these limitations, metaheuristic methods have gained significant attention in recent decades. These algorithms are particularly well suited for complex decision-making problems and are widely used in financial and banking applications involving large-scale combinatorial optimization. Consequently, they are often regarded as effective solution approaches for challenging real-world optimization problems [14]. Figure 5 presents a hierarchical classification of single-solution and population-based metaheuristic methods, illustrating their structural differences.

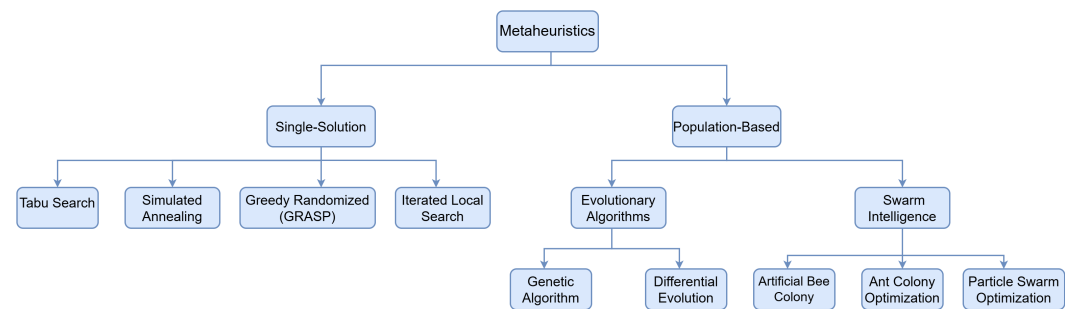


Figure 5. Hierarchical classification of metaheuristic algorithms.

5.1. Portfolio Optimization Under Constraints

Portfolio optimization is a classical problem in Management Science and Operations Research. The field began with the mean–variance portfolio selection model [116], which is formulated as a quadratic optimization problem with linear constraints. This basic model has several limitations that restrict its practical applicability, which has led to numerous extensions designed to incorporate features such as transaction costs, additional constraints, and alternative investment objectives. In the classical mean–variance framework, portfolio selection is treated as a multi-objective problem that seeks to maximize return while minimizing risk. In its standard formulation, the model reduces to a quadratic programming problem that generates optimal solutions along the efficient frontier. The problem can be expressed as follows:

$$\min w^T \Sigma w \quad (4)$$

subject to:

$$\sum_i w_i = 1, \quad \sum_i w_i r_i \geq R_{\text{target}}, \quad w_i \geq 0 \quad (5)$$

where w denotes the vector of asset weights, Σ is the covariance matrix of asset returns, r_i is the expected return of asset i , and R_{target} is the target portfolio return. Portfolio optimization is a relevant problem in contemporary financial and managerial decision making, as multiple objectives and practical constraints make the task of creating and managing a portfolio significantly more intricate, dealing with limited resources [117]. In general, optimization refers to the process of identifying the best solution to a problem subject to defined objectives and constraints [118]. In realistic settings, these constraints substantially increase the complexity of portfolio construction and management [119]. To address these challenges, a large body of literature has proposed metaheuristic algorithms for constrained portfolio optimization. Some authors incorporate cardinality and quantity constraints into the portfolio selection problem [120]. Cardinality constraints limit the number of assets included in the portfolio, while quantity constraints impose upper and lower bounds on asset weights. Other authors analyze the role of metaheuristics in solving the problem under such constraints [121]. Similarly, some works extend the mean–variance framework by introducing cardinality and allocation constraints at both asset and sector levels [122]. Their hybrid approach combines an evolutionary algorithm for asset selection with quadratic programming for weight optimization.

From a decision-making perspective, metaheuristic methods are particularly suitable for constrained portfolio optimization, as they enable the identification of high-quality feasible solutions in complex search spaces. In many practical applications, such near-optimal solutions are more useful than exact solutions derived from simplified models. The cardinality-constrained mean–variance problem is NP-complete [123], and its computational complexity increases exponentially with problem size. Some authors examine heuristic approaches such as GA, SA, and TS for solving the CCMV problem and show that cardinality constraints lead to a discontinuous efficient frontier [120]. Other studies

further extend the original model by incorporating additional cardinality and threshold constraints [124]. In this context, constraint handling is a critical issue in metaheuristic-based portfolio optimization. Realistic portfolio models typically include multiple interacting constraints that must be satisfied simultaneously. To ensure feasibility, repair and normalization techniques are commonly used to adjust candidate solutions during the search process, particularly for constraints related to budget balance, weight bounds, and asset allocation restrictions [125]. Table 4 summarizes the use of metaheuristic approaches for solving the portfolio optimization problem under realistic constraints.

Table 4. Metaheuristic-based portfolio optimization under realistic constraints.

Portfolio Problem	Constraints	Metaheuristic Technique	Dataset	Article
Mean–variance portfolio optimization	Cardinality/Minimum transaction lots/Sector capitalization	GA	Hang Seng, DAX 100, FTSE 100, S&P 100, Nikkei 225	[126]
Multiobjective portfolio optimization	Cardinality/Buy-in thresholds/Round lots/Asset-class constraints/Turnover constraints	DE	Italian Stock Exchange (219 stocks)	[127]
Enhanced index tracking portfolio	Sparsity (cardinality)/Transaction fees/Budget/Full-share restriction/Risk diversification	GA, PSO	S&P 100 Index	[121]
Rich mean–variance portfolio optimization	Cardinality/Quantity bounds/Pre-assignment/No short selling	Biased-Randomized Iterated Local Search	Hang Seng, DAX 100, FTSE 100, S&P 100, Nikkei 225	[128]
Constrained mean–variance portfolio optimization	Budget constraint/No short selling	PSO	SSE 50 Index (Shanghai Stock Exchange)	[129]
Mean–variance portfolio optimization	Cardinality	GA + ACO	Benchmark portfolio optimization instances	[130]
Multi-objective futures asset allocation	Risk budgeting/Capital budget/Asset-class bounds/Long/short bounds	DE	Historical futures returns (37 assets; 2004–2013)	[125]
Multi-objective portfolio optimization (VaR-based)	Cardinality/Quantity bounds/Budget constraint	PSO	S&P 500 daily returns	[131]
Mean–variance portfolio optimization	Cardinality/Budget constraint	GA	CSI 300 index (China)	[132]
Credit portfolio optimization	Default risk/Target return	GA	Markit iTraxx CDS index	[133]
Risk-budgeted portfolio optimization	Risk budgeting/Long–short/Leverage constraints	DE	Nifty50 monthly stock prices	[134]
Constrained mean–variance portfolio optimization	Cardinality/Bounds/Minimum transaction lots/Sector capitalization	PSO	Benchmark stock datasets (9, 30, 150 assets)	[135]

To provide a quantitative synthesis of the reviewed portfolio optimization literature, Table 5 presents the frequency of some metaheuristic techniques across the most commonly considered practical portfolio constraints. The results indicate that GA and PSO are the most widely used metaheuristic methods in the reviewed portfolio optimization studies, particularly for handling cardinality, budget, and no-short-selling constraints.

Table 5. Frequency of major metaheuristic techniques across commonly addressed practical portfolio constraints.

Technique	Portfolio Constraints					Long/Short
	Cardinality	Budget	No Short-Selling	Quantity Bounds	Transaction Costs	
GA	5	3	1		2	
PSO	3	4	2	2	1	
DE		1				2

The effectiveness of a given metaheuristic depends largely on the portfolio formulation and the set of constraints considered. GA-based methods have shown effectiveness in nonconvex and cardinality-constrained portfolio optimization problems. Multi-objective GA frameworks have been successfully applied to obtain efficient risk–return trade-offs in equity and credit portfolio optimization problems [130,133]. PSO algorithms have shown strong performance in tightly constrained and/or multiple-objective portfolio optimization problems with cardinality, sector capitalization, quantity, and value-at-risk constraints [131,135]. DE algorithms have shown strong performance in the risk-budgeted portfolio optimization problem and under long–short constraints in risk–return optimization [134].

5.2. Dynamic Asset–Liability Management

Asset–liability management (ALM) is a risk management problem in quantitative finance and actuarial science. Traditional ALM practices rely heavily on the expertise and judgment of professionals such as quantitative analysts, actuaries, and investment managers. While expert knowledge remains essential, this dependence on human decision-making can limit the effectiveness of ALM due to behavioral biases, limited automation, and restricted opportunities for systematic multi-objective optimization [136]. Unlike portfolio optimization, which focuses on determining a single asset allocation, ALM involves identifying a sequence of decisions or policies over a planning horizon. ALM is particularly relevant for financial institutions such as insurance companies and banks. In practice, these organizations must determine how to allocate assets to meet future liabilities while balancing profitability, risk, and regulatory requirements. However, the asset allocation policy that appears optimal under deterministic assumptions can become significantly suboptimal when uncertainty is incorporated into the decision-making process.

In recent years, the integration of simulation and metaheuristic optimization, commonly referred to as simheuristics [137], has attracted increasing attention as an effective approach for solving stochastic optimization problems. Consequently, simulation–optimization approaches have become increasingly relevant for ALM applications, where key model parameters are subject to uncertainty and cannot be adequately represented using deterministic values alone [138]. Simheuristic methods combine metaheuristic algorithms, which efficiently explore large and NP-hard combinatorial search spaces, with simulation techniques that explicitly represent uncertainty in objective functions and constraints. Although metaheuristics are traditionally developed for deterministic settings, some authors argue that deterministic formulations often oversimplify real-world decision environments [139]. By incorporating simulation into the optimization process, simheuris-

tics enable the evaluation of candidate solutions according to their stochastic performance, thereby providing information about both expected outcomes and associated risks. Typically, a deterministic heuristic is first employed to generate an initial solution. Subsequently, randomized metaheuristic search procedures explore alternative solutions within the feasible region. Simulation methods, including Monte Carlo simulation, are then used to evaluate the performance of candidate solutions under uncertainty [140]. Furthermore, simulation effort can be selectively intensified for promising solutions, leading to more accurate performance estimates. The information generated through these evaluations can then guide the search process toward solutions that are not only effective but also robust under uncertainty [139]. The simheuristic approach is particularly suitable for ALM applications, where liabilities are often modeled as stochastic variables [141]. In this context, the ALM problem can be formulated as a stochastic optimization problem in which asset returns, liability cash flows, and market conditions evolve under uncertainty over time. Consequently, the objective is not merely to identify an optimal allocation, but to develop decision policies that remain effective across a wide range of possible future scenarios [142]. Figure 6 illustrates the simulation–optimization architecture underlying simheuristic approaches, highlighting the interaction between optimization and simulation components to support the identification of high-quality and robust solutions in complex stochastic decision environments. The simulation component is used to evaluate generated solutions by a metaheuristic algorithm. The evaluation is performed on two stages: (i) fast evaluation to identify promising and elite solutions, and then (ii) more intensive evaluation to compare between solutions performance under different stochastic scenarios.

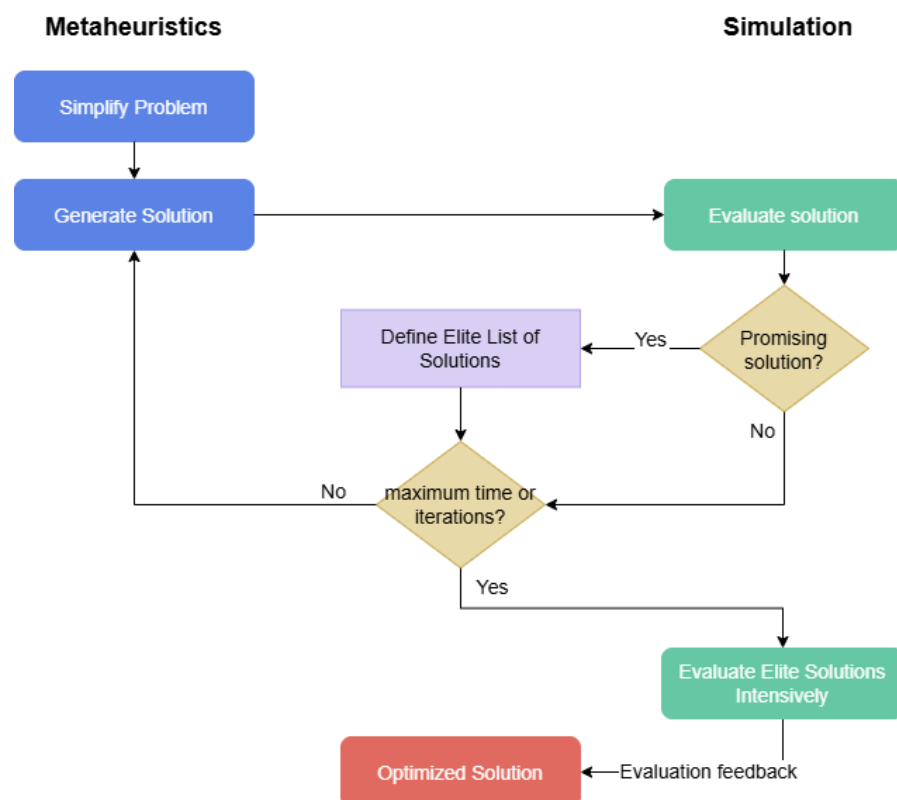


Figure 6. Simheuristic framework combining metaheuristic optimization and simulation.

Table 6 summarizes metaheuristic and simheuristic optimization techniques, which have been applied in the ALM field. The chosen articles show that the dynamic and constraint-sensitive characteristics of ALM decision-making are met by the use of metaheuristic search methods. Simheuristic techniques are further generalizations of these

methods and combine Monte Carlo simulation and metaheuristic optimization to deal with uncertainty and randomness.

Table 6. Metaheuristic and simheuristic approaches for ALM.

Optimization Approach	Optimization Techniques	Optimization Objective	Article
Simheuristic	Biased-randomized heuristic with Monte Carlo simulation	Asset–liability matching under reliability constraints	[138]
Simheuristic	Greedy constructive heuristics, biased-randomized algorithms, and Monte Carlo simulation	Asset–liability assignment, cash-flow matching	[141]
Metaheuristic	GA	Dynamic asset and liability management for pension funds	[143]

To illustrate our discussion of optimization-based decision-making applications, the essential objectives, constraints, and shared optimization attributes of portfolio optimization and ALM are depicted in Figure 7. The figure emphasizes that uncertainty plays a key role in both problems, as the decision-maker faces uncertainty and is confronted with various constraints. It also provides examples of the use of optimization techniques, including metaheuristics, simulation techniques, and simheuristic approaches, for assisting in robust decision-making under uncertain market conditions.

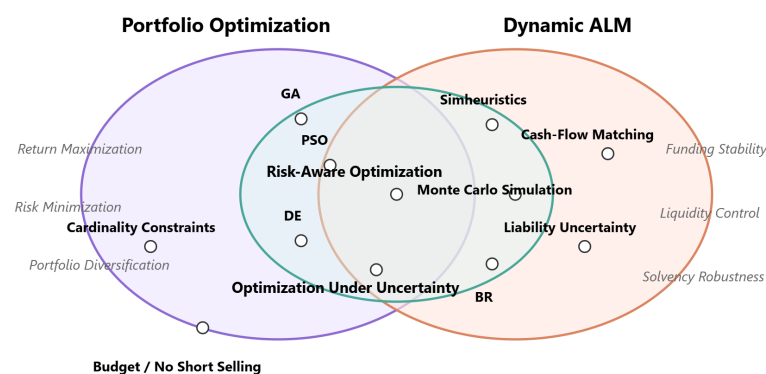


Figure 7. Framework of optimization-based financial decision-making applications in portfolio optimization and dynamic ALM under uncertainty and financial risk considerations.

6. Discussion and Research Gaps

The analysis presented in the preceding sections shows the growing importance of ML models in enhancing predictive analytics across a wide range of FinTech applications. At the same time, an expanding body of literature emphasizes the role of decision-oriented models that utilize predictive information to support complex financial decisions under uncertainty and operational constraints. ML enables financial institutions to extract insights from large volumes of data, thereby improving forecasting accuracy and reducing reliance on judgment-based decision-making. Applications such as market forecasting, portfolio management, and financial risk assessment have shown the ability of ML algorithms to capture nonlinear relationships and complex patterns that are difficult to identify using traditional statistical methods. In addition, deep learning models have improved credit assessment processes by incorporating large-scale and heterogeneous data sources, thereby

supporting more inclusive financial services. This transformation is also reflected in the growth of algorithmic trading systems, where AI-driven models continuously adapt to changing market conditions and support automated decision-making. Despite these advances, several challenges remain associated with the integration of ML into financial decision-making. Key concerns include model interpretability, robustness, governance, and regulatory compliance. These challenges become particularly significant when ML-based predictions are incorporated into financial decisions that must be made under market uncertainty and subject to complex operational and regulatory constraints.

The presence of multiple interacting constraints substantially increases the difficulty of identifying optimal or near-optimal financial decisions, especially in large-scale applications. In this context, metaheuristic methods have emerged as effective optimization tools due to their flexibility in handling complex objective functions, diverse constraint structures, and high-dimensional search spaces. As approximate optimization methods, metaheuristics can generate high-quality solutions with reasonable computational effort for a broad range of combinatorial optimization problems. They are particularly valuable when exact optimization methods become computationally prohibitive or require unrealistic simplifying assumptions. Nevertheless, a gap remains between the needs of practitioners and the current capabilities of optimization methodologies, particularly with respect to scalability, interpretability, and real-time implementation.

A major source of this gap is the separation between predictive modeling and optimization-based decision-making. Most ML studies focus on maximizing predictive performance using out-of-sample evaluation criteria. In contrast, optimization models typically assume that key inputs, such as expected returns, volatilities, or default probabilities, are externally provided and remain fixed throughout the decision process. In real-world financial environments, however, prediction errors directly affect decision variables, including portfolio allocations, risk exposures, and liability-matching strategies. Consequently, model uncertainty and estimation risk become embedded within the optimization process itself. Although recent research has explored hybrid predictive-optimization frameworks, limited attention has been given to integrating predictive uncertainty into constraint-sensitive and multi-period financial decision models. Although research on predictive analytics and optimization-based decision making under uncertainty is abundant in distinct research areas, the integration of both within a single financial decision support framework has received limited attention. Several methods have been suggested to assist financial decisions in the presence of uncertainty, but they have not yet been widely adopted, and are not widely integrated into financial decision support systems. This leaves a methodological gap between predictive analytics and optimization-based decision-making. Therefore, further research is needed on how to develop integrated frameworks that incorporate ML-based predictive models and optimization procedures explicitly considering uncertainty and risk. One promising research direction is the development of more comprehensive systems for financial decision-making that incorporate the ML models for forecasting important financial indicators, including stock prices, asset returns, volatility, default probabilities, and fraud risks. Such predictions and the corresponding uncertainty estimates can then serve as inputs to optimization models for financial decision-making applications.

Furthermore, many combinatorial optimization problems in finance and banking continue to be formulated using static and deterministic models. Such formulations fail to capture the uncertainty and dynamic behavior that characterize real-world financial systems, including stochastic asset returns, evolving market conditions, and uncertain liability streams. A primary reason for this simplification is the additional computational complexity introduced by stochastic components [115]. In this context, the integration of simulations, ML, and metaheuristic optimization offers a promising direction for future

research, as it enables uncertainty to be explicitly modeled while evaluating the robustness and reliability of candidate solutions under realistic operating conditions.

7. Conclusions

This paper reviewed the applications of AI, ML, and metaheuristic optimization in FinTech and examined how these technologies contribute to both predictive analytics and optimization-based financial decision support. The reviewed literature indicates that AI and ML have become key enablers of data-driven finance, supporting a wide range of applications including financial forecasting, stock price prediction, risk management, and fraud detection. Beyond predictive analytics, the survey shows a growing interest in optimization-based approaches that transform predictive information into actionable decisions. In this context, metaheuristic optimization methods have emerged as effective tools for solving large-scale and complex financial optimization problems, particularly those involving multiple objectives, practical constraints, and uncertain environments. The paper highlights the importance of explicitly accounting for uncertainty in financial systems. Real-world financial decisions are affected by stochastic market behavior, changing economic conditions, and imperfect information. Consequently, simulation-based approaches provide an additional layer of analysis by enabling the evaluation of solution quality, robustness, and risk under uncertain scenarios. The growing adoption of simheuristic approaches illustrates the potential of combining optimization and simulation to support more realistic financial decision-making.

This review revealed that AI and ML have been key technologies in FinTech and have a wide range of applications, such as financial forecasting, stock price prediction, financial risk management, and fraud detection. The paper also shows that the metaheuristic and simheuristic techniques are effective tools in solving complex financial decision-making problems involving multiple objectives, practical constraints and uncertainty. Lastly, the paper shows the growing need for including the prediction and uncertainty estimates derived from AI and ML models in financial optimization processes, thus allowing robust and informed financial decision-making. The study reveals several promising directions for future research. In particular, there is a need for integrated decision-support systems capable of addressing the increasing complexity of modern financial environments, which are characterized by uncertainty, dynamic behavior, and multiple interacting constraints. While significant progress has been made in both predictive analytics and optimization, these research streams have largely evolved independently. Constrained and multi-objective portfolio optimization represents a natural setting for integrating predictive analytics with advanced optimization methods. By combining ML-based forecasting models with optimization techniques, financial institutions can develop more adaptive, robust, and data-driven decision processes. These ideas can be further extended to ALM, where portfolio optimization forms only one component of a broader strategic framework that coordinates asset allocation, liability management, and financial risk control over multiple planning periods. Finally, the paper also identifies a significant research gap in the integration of predictive models, optimization methods, and simulation-based analysis within unified financial decision-support frameworks. Bridging the current separation between prediction and optimization, while explicitly accounting for uncertainty in multi-period and constraint-sensitive environments, represents an important direction for future FinTech research.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
SVMs	Support Vector Machines
RFs	Random Forests
GB	Gradient Boosting
RL	Reinforcement Learning
GAs	Genetic Algorithms
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimization
SA	Simulated Annealing
TS	Tabu Search
DE	Differential Evolution
LSTM	Long Short-Term Memory
NLP	Natural Language Processing
ANN	Artificial Neural Network
XAI	Explainable Artificial Intelligence
LLMs	Large Language Models
MSE	Mean Squared Error
SVR	Support Vector Regression
EAs	Evolutionary Algorithms
ALM	Asset–Liability Management

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