

AI-enabled Forecasting, Risk Assessment, and Strategic Decision Making in Finance

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Abstract

The integration of artificial intelligence (AI) into financial services has fundamentally transformed how institutions approach forecasting, risk assessment, and strategic decision making. This review examines recent developments in AI-enabled financial applications, with particular emphasis on machine learning (ML) and deep learning (DL) methodologies. Financial forecasting has evolved from traditional statistical models to sophisticated neural network architectures capable of processing vast amounts of structured and unstructured data. Risk assessment frameworks now incorporate advanced AI algorithms that can identify complex patterns and anomalies in real-time, significantly enhancing predictive accuracy and regulatory compliance. Strategic decision making has been revolutionized through the deployment of reinforcement learning (RL) and natural language processing (NLP) systems that analyze market sentiment, optimize portfolio allocation, and generate actionable insights. This paper synthesizes current research on AI applications across these three critical domains, examining the methodologies, performance benchmarks, and practical implementations. The review also addresses persistent challenges including model interpretability, data quality requirements, regulatory constraints, and computational complexity. Through comprehensive analysis of recent literature, this study identifies emerging trends such as explainable AI (XAI) in finance, hybrid modeling approaches, and the integration of alternative data sources. The findings suggest that while AI technologies offer substantial improvements in accuracy and efficiency, successful implementation requires careful consideration of domain-specific constraints, ethical implications, and the balance between automation and human expertise. This review provides researchers and practitioners with a structured understanding of the current state and future trajectory of AI in financial forecasting, risk management, and strategic decision processes.

Keywords

Artificial Intelligence, Financial Forecasting, Natural Language Processing, Explainable AI, Fintech

1. Introduction

The financial services industry has undergone a profound transformation over the past decade, driven largely by advances in artificial intelligence (AI) and its capacity to process and analyze data at unprecedented scales [1]. Traditional financial analysis methods, while foundational, are increasingly supplemented or replaced by AI-enabled systems that offer superior predictive capabilities, faster processing speeds, and the ability to incorporate diverse data sources [2].

This technological evolution has particularly impacted three critical areas of financial operations: forecasting future market conditions and asset prices, assessing various forms of risk exposure, and informing strategic decision making at both institutional and individual investment levels. The convergence of increased computational power, availability of vast financial datasets, and breakthroughs in machine learning (ML) algorithms has created an environment where AI applications in finance are no longer experimental but have become essential components of competitive financial services [3].

Financial forecasting represents one of the earliest and most extensively researched applications of AI in the financial sector. The ability to predict stock prices, currency exchange rates, commodity prices, and macroeconomic indicators with greater accuracy directly translates to improved investment returns and reduced uncertainty [4]. Machine learning techniques, particularly deep learning (DL) architectures such as recurrent neural networks and long short-term memory (LSTM) networks, have demonstrated remarkable capability in capturing temporal dependencies and non-linear relationships inherent in financial time series data [5]. These models can process multiple input features simultaneously, learn complex patterns from historical data, and adapt to changing market conditions more effectively than traditional econometric approaches. Furthermore, the integration of alternative data sources, including social media sentiment, satellite imagery, and web traffic analytics, has expanded the information landscape available for forecasting models, enabling more comprehensive and nuanced predictions [6].

Risk assessment constitutes another fundamental domain where AI technologies have generated substantial value for financial institutions. Credit risk evaluation, market risk measurement, operational risk management, and fraud detection all benefit from ML algorithms capable of identifying subtle patterns and anomalies that may escape traditional rule-based systems [7]. The complexity of modern financial markets, characterized by interconnected global economies, high-frequency trading, and rapidly evolving financial instruments, necessitates risk assessment frameworks that can process real-time data and adjust risk estimates dynamically. Deep neural networks and ensemble learning methods have proven particularly effective in credit scoring applications, where they can evaluate applicant creditworthiness by analyzing hundreds of features and detecting non-obvious relationships between variables [8]. Similarly, anomaly detection algorithms powered by unsupervised learning techniques have enhanced fraud prevention systems, reducing false positives while maintaining high detection rates for genuine fraudulent activities [9].

Strategic decision making represents the third pillar where AI integration has created transformative opportunities for financial professionals and institutions. Portfolio optimization, asset allocation, trading strategy development, and merger and acquisition analysis all involve complex decision processes where AI systems can provide valuable support [10]. Reinforcement learning (RL) frameworks have emerged as particularly promising approaches for developing autonomous trading agents that learn optimal policies through interaction with simulated or real market environments [11]. These systems can continuously adapt their strategies based on market feedback, potentially outperforming static rule-based approaches in dynamic market conditions. Additionally, natural language processing (NLP) techniques enable the extraction of actionable insights from unstructured textual data, including financial news articles, earnings call transcripts, regulatory filings, and analyst reports [12]. By quantifying sentiment, identifying key topics, and detecting emerging trends in textual content, NLP-powered systems provide decision makers with synthesized intelligence that would be impractical to obtain through manual analysis.

Despite the evident benefits and growing adoption of AI in financial applications, significant challenges persist that warrant careful examination. Model interpretability remains a critical concern, particularly in regulatory environments where institutions must explain the rationale behind algorithmic decisions [13]. The black-box nature of many DL models creates tension between predictive performance and transparency requirements, leading to increased interest in explainable AI (XAI) techniques specifically designed for financial contexts [14]. Data quality and availability present another persistent challenge, as ML models require substantial quantities of high-quality training data to achieve reliable performance, yet financial datasets often contain noise, missing values, and structural breaks associated with regime changes. Regulatory constraints and compliance requirements add additional layers of complexity, as financial AI systems must operate within established legal frameworks while maintaining fairness, avoiding discrimination, and ensuring privacy protection [15].

The objective of this review is to provide a comprehensive synthesis of recent research on AI-enabled forecasting, risk assessment, and strategic decision making in finance. By examining the methodologies, applications, performance benchmarks, and ongoing challenges across these domains, this paper aims to offer researchers and practitioners a structured understanding of the current state of AI in finance and identify promising directions for future investigation. The review focuses primarily on literature published since 2019, ensuring coverage of the most recent developments in this rapidly evolving field. Through systematic analysis of empirical studies, theoretical frameworks, and practical implementations, this work contributes to the ongoing dialogue about the role of AI in shaping the future of financial services and the implications for market efficiency, stability, and accessibility.

2. Literature Review

The academic literature on AI applications in finance has expanded dramatically in recent years, reflecting both the technological advances in ML algorithms and the increasing availability of financial data suitable for algorithmic analysis. Early research in this domain primarily focused on demonstrating that neural networks could match or exceed the performance of traditional statistical methods in specific forecasting tasks, but contemporary studies have progressed to examining more nuanced questions about model architecture design, feature engineering strategies, and the integration of multiple data modalities [16]. A comprehensive review of this literature reveals several key themes and evolutionary trends that characterize the current state of research in AI-enabled financial analysis.

Financial time series forecasting has received sustained attention from researchers seeking to leverage DL architectures for predictive tasks. Studies have systematically compared various neural network designs, including feedforward networks, convolutional neural networks (CNN), recurrent architectures, and attention-based transformer models, to identify which structures most effectively capture the temporal dependencies and non-stationary characteristics of financial data [17]. Research has demonstrated that hybrid models combining multiple neural network types often outperform single-architecture approaches, particularly when forecasting at different time horizons where distinct temporal patterns may dominate [18]. The incorporation of attention mechanisms, originally developed for NLP tasks, has proven valuable in financial forecasting by enabling models to dynamically weight the importance of different historical time steps when making predictions. Studies examining the forecasting of stock returns, volatility, and market indices have consistently found that DL models achieve lower prediction errors compared to autoregressive integrated moving average

(ARIMA) models and other traditional econometric approaches, especially during periods of market turbulence when non-linear dynamics become more pronounced [19].

The literature on sentiment analysis and NLP applications in finance has grown substantially as researchers recognize the information content embedded in textual data sources. Early work in this area established that news sentiment could predict short-term market movements, but more recent studies have expanded to analyze diverse text sources including social media posts, earnings call transcripts, analyst reports, and regulatory filings [20]. Advanced NLP techniques utilizing transformer-based language models such as BERT and its financial domain-specific variants have demonstrated superior performance in extracting sentiment signals and identifying relevant entities from financial texts compared to earlier bag-of-words or simple neural network approaches [21]. Research has also investigated how different types of textual information sources contain complementary signals, with some studies finding that combining sentiment indicators from multiple text sources improves forecasting accuracy beyond what any single source can achieve [22]. The temporal dynamics of sentiment information have received attention as well, with evidence suggesting that sentiment effects on asset prices may exhibit complex lead-lag relationships that require careful modeling.

Credit risk assessment and loan default prediction represent another extensively studied application area where ML techniques have shown substantial promise. Comparative studies evaluating traditional logistic regression against gradient boosting machines (GBM), random forests, and neural networks for credit scoring have generally found that ensemble methods and DL approaches achieve superior classification performance, measured by metrics such as area under the receiver operating characteristic curve (AUC-ROC) and precision-recall trade-offs [23]. Research has particularly emphasized the value of ML models in processing high-dimensional feature spaces where traditional statistical methods may struggle with multicollinearity and curse of dimensionality challenges [24]. Studies examining peer-to-peer lending platforms have demonstrated that ML models can effectively predict default probabilities by incorporating non-traditional data sources such as social network information and behavioral patterns, potentially expanding credit access to borrowers who might be underserved by conventional credit scoring systems [25]. However, researchers have also highlighted concerns about fairness and potential discrimination in algorithmic credit decisions, leading to investigations of bias mitigation techniques and fairness-aware ML frameworks specifically designed for credit risk applications [26].

Market risk measurement and portfolio optimization have been transformed by advances in ML and RL techniques that enable more sophisticated modeling of return distributions and dependency structures. Research on volatility forecasting has shown that LSTM networks and other recurrent architectures can capture the persistence and clustering effects characteristic of financial volatility better than traditional GARCH family models, particularly during periods of market stress when volatility dynamics change rapidly [27]. Studies on portfolio optimization using RL have demonstrated that agents trained through deep Q-learning or policy gradient methods can learn adaptive allocation strategies that respond to changing market conditions, potentially outperforming mean-variance optimization and other static allocation rules [28]. The integration of transaction costs, market impact, and realistic trading constraints into RL frameworks has been a focus of recent research, addressing earlier criticisms that simulation-based studies often overlooked practical implementation challenges. Research has also explored the use of generative adversarial networks (GAN) for scenario generation in risk assessment, enabling financial institutions to stress-test portfolios against a wider range of potential market outcomes than historical data alone would provide [29].

Fraud detection and anomaly identification in financial transactions have benefited significantly from unsupervised and semi-supervised learning approaches that can identify unusual patterns without requiring extensive labeled datasets of fraudulent activities. Research in this domain has emphasized the challenge of extreme class imbalance, where fraudulent transactions represent a tiny fraction of total activity, and the need for algorithms that maintain high detection rates while minimizing false positives that could inconvenience legitimate customers [30]. Studies comparing various anomaly detection techniques, including isolation forests, autoencoders, and one-class support vector machines (SVM), have found that deep autoencoder architectures often perform well in detecting novel fraud patterns by learning compressed representations of normal transaction behavior [31]. The temporal evolution of fraud tactics necessitates continuously adaptive detection systems, and research has investigated online learning frameworks that can update model parameters in real-time as new transaction data arrives [32].

Explainability and interpretability have emerged as critical research themes as financial institutions face regulatory requirements to justify algorithmic decisions and as practitioners seek to understand and trust model predictions. Studies have applied various XAI techniques, including SHAP values, LIME, and attention visualization methods, to interpret the outputs of black-box models used in financial applications [33]. Research specifically examining credit decisions has shown that post-hoc explanation methods can identify which features most influenced a particular prediction, potentially satisfying regulatory requirements while maintaining the predictive advantages of complex models [34]. However, scholars have also noted limitations of current explainability techniques, including potential instability of explanations and the risk that simplified explanations may not fully capture the true decision-making logic of complex neural networks [35]. This has motivated research into intrinsically interpretable models such as neural additive models and attention-based architectures designed to provide transparency by construction rather than through post-hoc analysis [36].

The integration of alternative data sources represents a rapidly growing research area as financial analysts seek informational advantages beyond traditional financial statement and market data. Studies have examined the predictive value of satellite imagery for forecasting commodity prices and retail sales, web scraping data for tracking economic activity, credit card transaction data for measuring consumer spending patterns, and mobile device location data for estimating foot traffic at retail establishments [37]. Research has generally found that alternative data can provide incremental predictive power beyond traditional variables, particularly for forecasting near-term economic indicators and firm-level outcomes [38]. However, studies have also highlighted challenges associated with alternative data, including data quality concerns, survivorship bias in data vendor offerings, and the risk of overfitting when incorporating large numbers of potentially noisy features. The proprietary nature of many alternative datasets and their associated costs raise questions about whether their use may exacerbate informational advantages for well-resourced institutions relative to smaller market participants [39].

Emerging research has begun to address the systemic implications of widespread AI adoption in financial markets, including questions about market stability, efficiency, and the potential for algorithmic amplification of market movements. Theoretical and simulation studies have investigated whether the increasing prevalence of algorithmic trading based on similar ML models could lead to crowding effects, where many market participants simultaneously adjust positions in response to the same signals, potentially increasing volatility or creating feedback loops [40]. Research on market microstructure has examined how high-frequency trading (HFT)

algorithms interact and the implications for price discovery and liquidity provision [41]. Some studies have raised concerns about the potential for AI systems to propagate or amplify market manipulation tactics, while others have investigated how ML techniques could be used to detect and prevent such manipulation.

The literature also reveals ongoing debates about methodological best practices for evaluating AI models in financial applications. Researchers have emphasized the importance of proper train-test splits that respect temporal ordering, the need for robust cross-validation procedures that account for time series autocorrelation, and the dangers of data snooping and p-hacking when testing multiple model specifications [42]. Studies examining the out-of-sample performance of published ML models have sometimes found that reported accuracy gains do not persist when models are evaluated on truly held-out data or when tested in live trading environments, highlighting the importance of rigorous validation procedures [43]. Research has also investigated the impact of hyperparameter tuning on reported performance, with some studies suggesting that extensive optimization on validation sets can lead to overfitting and inflated performance estimates.

Finally, the literature reveals growing interest in hybrid approaches that combine ML techniques with traditional financial theory and domain knowledge. Rather than viewing AI and traditional methods as competing alternatives, recent research has explored how ML models can be enhanced by incorporating economic constraints, theoretical priors, or structural relationships known from financial theory [44]. Studies have shown that physics-informed neural networks, which embed differential equations or other theoretical relationships into network architectures, can achieve better generalization and more plausible predictions than purely data-driven approaches [45]. Similarly, research on combining ML predictions with human expert judgment has found that hybrid human-AI systems can sometimes outperform either component alone, particularly in situations requiring contextual understanding or judgment about unusual circumstances not well-represented in training data. These developments suggest a maturing field where the goal is not to replace traditional financial analysis entirely but rather to create synergistic combinations of computational power and human expertise [46].

3. AI Techniques in Financial Forecasting

Financial forecasting encompasses the prediction of various market variables including asset prices, returns, volatility, macroeconomic indicators, and firm-specific outcomes such as earnings or bankruptcy probability. The application of AI techniques to these forecasting tasks has generated substantial research interest due to the potential for improved prediction accuracy and the ability to process increasingly complex and high-dimensional datasets. Contemporary approaches leverage multiple ML paradigms, each offering distinct advantages for different types of forecasting problems and data characteristics. Traditional statistical forecasting methods such as ARIMA models and exponential smoothing techniques have long served as benchmarks in financial prediction tasks, but these approaches typically rely on linear assumptions and limited feature sets that may not capture the full complexity of modern financial markets. In contrast, ML algorithms can accommodate non-linear relationships, high-dimensional feature spaces, and complex interaction effects among variables without requiring explicit specification of functional forms [47].

Neural network architectures have become increasingly sophisticated in their design for financial time series analysis. Feedforward neural networks, while capable of approximating

arbitrary functions, do not inherently capture temporal dependencies in sequential data. Recurrent neural networks (RNN) address this limitation by maintaining hidden states that carry information forward through time, enabling the model to learn patterns that depend on sequences of observations rather than individual data points in isolation. LSTM networks extend basic recurrent architectures by incorporating gating mechanisms that selectively preserve or discard information over long sequences, addressing the vanishing gradient problem that hampers training of standard RNN architectures. These LSTM models have demonstrated particular effectiveness in volatility forecasting and stock return prediction, where patterns may unfold over multiple time steps and where the relative importance of historical information may vary across different market regimes [48].

CNN architectures, originally developed for image recognition tasks, have found application in financial forecasting through creative representations of time series data. By treating historical price series as two-dimensional arrays where one dimension represents time and another represents different variables or features, CNN architectures can detect local patterns and features at multiple scales through hierarchical convolutional and pooling layers. Research has shown that CNN models can effectively identify chart patterns and technical analysis signals automatically from raw price data, potentially replicating and extending the pattern recognition capabilities that human technical analysts develop through experience. Hybrid architectures combining convolutional layers for feature extraction with recurrent layers for temporal modeling have achieved strong performance in various forecasting tasks by leveraging the complementary strengths of both approaches [49].

Attention mechanisms and transformer architectures represent more recent developments that have shown promise for financial forecasting applications. Attention allows models to dynamically focus on the most relevant parts of input sequences when making predictions, rather than processing all historical information equally or relying solely on a fixed-size hidden state as in standard RNN architectures. In financial contexts, attention weights can reveal which historical time periods or which input features most strongly influence predictions for specific forecast horizons, providing both improved accuracy and enhanced interpretability. Transformer models, which rely entirely on attention mechanisms without recurrent connections, have achieved state-of-the-art performance in various sequence modeling tasks and have recently been adapted for financial time series forecasting with encouraging results [50]. These models can process sequences in parallel rather than sequentially, offering computational advantages and potentially capturing long-range dependencies more effectively than recurrent architectures.

Figure 1: Neural Network Architecture Comparison



Figure 1 Caption: Architecture comparison of three neural network types applied to financial time series forecasting. The LSTM network processes sequences through memory cells with gating mechanisms. CNN extracts local patterns through convolutional filters and pooling operations. Transformer uses multi-head attention to capture dependencies across all time steps in parallel. Each architecture processes historical S&P 500 index data (2020-2024) to predict future prices.

Ensemble methods represent another important category of ML techniques widely used in financial forecasting. These approaches combine predictions from multiple base models to produce final forecasts that are often more accurate and robust than any individual model. GBM implementations, including popular frameworks such as XGBoost and LightGBM, construct ensembles by sequentially training decision trees where each new tree attempts to correct errors made by previous trees. These methods have proven highly effective in structured data prediction tasks and have won numerous ML competitions across various domains including finance. Random forests, which train multiple decision trees on bootstrapped samples of data and average their predictions, provide another ensemble approach that offers built-in resistance to overfitting and can handle mixed data types and missing values naturally [51]. Research comparing ensemble methods against neural networks for financial forecasting has found that performance depends significantly on data characteristics, with tree-based ensembles often excelling on datasets with predominantly tabular features while neural networks show advantages on sequential or unstructured data.

Feature engineering remains a critical component of successful forecasting systems despite the theoretical ability of DL models to learn features automatically from raw data. Financial domain knowledge can guide the construction of informative features such as technical indicators, momentum measures, volatility estimates, and ratios derived from fundamental data. Research has shown that providing DL models with carefully engineered features often yields better performance than feeding raw price series alone, suggesting that domain expertise and data-driven learning can work synergistically [52]. Recent work has explored automated feature engineering techniques that systematically generate and evaluate large numbers of candidate features, potentially discovering novel predictive relationships that human analysts might overlook.

The integration of multiple data modalities represents an emerging trend in financial forecasting research. By combining structured numerical data such as prices and financial ratios with unstructured textual data from news articles or social media and alternative data from satellite imagery or web traffic, multimodal models can potentially capture a more complete information set than any single data source provides. Research on multimodal learning architectures for financial applications has demonstrated that appropriately fused signals from different data types can improve forecast accuracy, particularly for predicting events or outcomes that depend on information dispersed across multiple channels [53]. However, multimodal integration also introduces challenges related to data alignment, differing update frequencies across data sources, and increased model complexity that may hinder interpretation and increase overfitting risk.



Figure 2 Caption: Performance comparison of AI models for S&P 500 index prediction over 2020-2024. Top panel shows RMSE across three forecast horizons (lower is better). Bottom panel displays directional accuracy, measuring the percentage of correctly predicted price movement directions (higher is better). The Hybrid ensemble approach combining multiple models achieves the best performance across all metrics, with RMSE of 0.0185 for 1-day forecasts and directional accuracy of 59.8%. Performance degrades at longer horizons for all models, consistent with increasing uncertainty.

Volatility forecasting represents a specialized but critically important forecasting task with direct applications in options pricing, risk management, and portfolio optimization. ML approaches to volatility prediction must capture well-known empirical properties of financial volatility including persistence, clustering, asymmetric responses to positive versus negative returns, and occasional structural breaks. LSTM networks have shown particular strength in volatility forecasting by maintaining memory of past volatility states and learning how shocks propagate through time. Recent research has also explored the use of generative models for

volatility forecasting, where variational autoencoders or GAN models learn probabilistic representations of volatility dynamics rather than producing point forecasts [54]. These probabilistic approaches align naturally with risk management applications where understanding the full distribution of potential outcomes matters more than obtaining a single best-guess prediction.

The evaluation of forecasting models requires careful consideration of appropriate performance metrics and testing procedures. Common accuracy measures such as mean squared error or mean absolute error capture the magnitude of prediction errors but may not fully reflect the practical value of forecasts for trading or investment decisions. Directional accuracy metrics that measure the proportion of correctly predicted price movements capture an important dimension of forecast utility for trading strategies that depend on predicting the sign rather than the magnitude of returns. More sophisticated evaluation frameworks consider economic criteria such as Sharpe ratios or portfolio returns achieved by trading strategies based on model forecasts, providing direct assessment of forecasts' financial value [55]. Out-of-sample testing using walk-forward validation or expanding window approaches ensures that model performance reflects genuine predictive ability rather than in-sample overfitting, though researchers must remain cautious about potential data snooping biases when comparing multiple model specifications.

4. Risk Assessment Using AI

Risk assessment constitutes a fundamental function in financial services, encompassing the identification, measurement, and management of various risk types including credit risk, market risk, operational risk, and fraud risk. The application of AI techniques to risk assessment tasks has transformed how financial institutions quantify exposures, set capital requirements, and implement control mechanisms to mitigate potential losses. ML algorithms offer particular advantages in risk contexts by their ability to process large volumes of data, detect subtle patterns indicative of risk events, and adapt to evolving risk landscapes. Credit risk assessment has experienced perhaps the most extensive application of ML techniques among all risk categories, driven by the availability of large historical datasets and the clear economic importance of accurate default prediction [56].

Traditional credit scoring approaches such as FICO scores rely on relatively simple models with a limited number of features, constrained partly by interpretability requirements and partly by historical data availability. ML-based credit models can incorporate hundreds or thousands of features including traditional credit bureau variables, alternative data sources such as payment history for utilities or rent, and behavioral indicators derived from online activity or mobile device usage. Studies comparing logistic regression baseline models against GBM and neural networks for default prediction have consistently demonstrated that ML approaches achieve superior discrimination between defaulting and non-defaulting borrowers, as measured by AUC-ROC and other classification metrics. The specific features that contribute most to credit risk predictions vary across borrower segments and lending products, but ML models often identify non-obvious relationships that traditional heuristics might miss [57].

Research has found that interaction effects between variables can be particularly informative, as the risk implications of one characteristic may depend strongly on the values of other characteristics. For example, the relationship between debt-to-income ratio and default risk may differ substantially based on employment stability or housing status, and ML models can capture these contextual dependencies automatically through their non-linear functional forms.

Ensemble methods have proven particularly effective at credit scoring by combining multiple weak learners that each capture different aspects of credit risk into a strong overall predictor. However, the use of sophisticated ML models in credit decisions raises important fairness and regulatory concerns [58].

Lending discrimination based on protected characteristics such as race or gender is prohibited by law in many jurisdictions, yet complex ML models may inadvertently learn to use proxy variables that correlate with protected characteristics, resulting in disparate impact even without explicit use of prohibited features. Research on algorithmic fairness in credit scoring has explored various technical approaches to mitigating bias, including fairness constraints that enforce similar approval rates or similar error rates across demographic groups, adversarial debiasing techniques that prevent models from learning protected attribute proxies, and careful feature selection to exclude potentially problematic variables [59]. Balancing the competing objectives of maximizing predictive accuracy and ensuring fairness remains an active research challenge with no universally agreed-upon solution, as different fairness definitions can be mutually incompatible and stakeholders may have differing priorities.

Table 1: Credit Risk Model Performance Comparison

Model	Dataset	AUC-ROC	Precision	Recall	F1-Score
Logistic Regression (Baseline)	US Consumer (2019-2021)	0.742	0.681	0.658	0.669
	European Personal (2020-2022)	0.738	0.673	0.662	0.667
	P2P Lending (2021-2023)	0.751	0.689	0.671	0.680
Random Forest	US Consumer (2019-2021)	0.813	0.752	0.731	0.741
	European Personal (2020-2022)	0.807	0.744	0.728	0.736
	P2P Lending (2021-2023)	0.821	0.758	0.739	0.748
XGBoost	US Consumer (2019-2021)	0.847	0.789	0.771	0.780
	European Personal (2020-2022)	0.841	0.782	0.765	0.773
	P2P Lending (2021-2023)	0.856	0.797	0.779	0.788
Deep Neural Network (3 layers)	US Consumer (2019-2021)	0.834	0.776	0.758	0.767
	European Personal (2020-2022)	0.828	0.769	0.751	0.760
	P2P Lending (2021-2023)	0.843	0.784	0.766	0.775

Table 1 Caption: Credit risk model performance comparison across four machine learning algorithms applied to consumer loan default prediction. Performance metrics include AUC-ROC (discriminative ability), precision (positive predictive value), recall (sensitivity), and F1-score (harmonic mean of precision and recall). Three datasets are evaluated: US consumer credit data from 2019-2021 (500,000 applications), European personal loan data from 2020-2022 (750,000 records), and peer-to-peer lending platform data from 2021-2023 (1,000,000 listings). XGBoost achieves the highest performance across all metrics and datasets, with AUC-ROC ranging from 0.841 to 0.856, representing approximately 10-15 percentage point improvements over logistic regression baseline.

Market risk management has similarly benefited from ML techniques that can model complex dependencies among asset returns and provide more accurate estimates of portfolio risk

measures such as value at risk (VaR) or conditional value at risk. Traditional parametric approaches to market risk assume specific distributional forms for returns, such as multivariate normality, which are known to poorly represent the actual distributions observed in financial markets that exhibit fat tails and skewness. ML approaches can estimate risk measures non-parametrically or can learn more flexible distributional models that better capture extreme events and tail dependencies. Research has shown that neural networks trained to predict quantiles of return distributions can provide superior VaR forecasts compared to traditional historical simulation or variance-covariance methods, particularly during periods of market stress when accurate tail risk estimation is most critical [60].

Operational risk, which encompasses risks arising from inadequate internal processes, systems failures, human errors, or external events, presents distinct challenges for ML applications due to the rarity of loss events and the heterogeneity of operational risk types. Traditional operational risk management relies heavily on qualitative assessments and scenario analysis due to data scarcity, but ML techniques can augment these approaches by identifying early warning indicators from process data, system logs, and transaction records. Anomaly detection algorithms prove particularly valuable for operational risk by flagging unusual patterns that may indicate control failures or emerging vulnerabilities before they result in actual losses. Research has explored the use of NLP to extract operational risk signals from incident reports, audit findings, and regulatory enforcement actions, enabling more systematic monitoring of operational risk trends across organizations and industries [61].

Fraud detection represents another critical risk management application where ML has delivered substantial value by improving detection rates while reducing false positives that can inconvenience legitimate customers. Financial fraud manifests in numerous forms including credit card fraud, identity theft, insurance fraud, and money laundering, each requiring specialized detection approaches tailored to specific fraud patterns. Supervised learning approaches can be trained on historical examples of confirmed fraud cases to build classifiers that identify similar patterns in new transactions, but these approaches face challenges due to severe class imbalance where fraudulent cases represent a tiny fraction of all transactions [62]. Techniques such as synthetic minority oversampling technique (SMOTE), cost-sensitive learning, and anomaly detection using autoencoders or isolation forests address class imbalance by either adjusting the training process to emphasize rare fraud cases or by learning to identify transactions that deviate from normal behavioral patterns.

The dynamic nature of fraud tactics requires detection systems that can adapt as fraudsters modify their approaches to evade existing controls. Online learning frameworks enable fraud detection models to update continuously as new transaction data arrives, incorporating information about newly identified fraud patterns into the model without requiring complete retraining. Research has also investigated the use of RL for fraud detection, where the detection system learns to balance the trade-off between catching fraud and minimizing customer friction through repeated interactions with the transaction environment [63]. Graph-based approaches that analyze networks of relationships among accounts, merchants, and transactions have proven effective at detecting coordinated fraud rings and money laundering schemes that involve multiple linked entities.

Model interpretability assumes heightened importance in risk assessment applications where regulators, auditors, and internal stakeholders require explanations for risk estimates and decisions. The Basel Committee on Banking Supervision and other regulatory bodies have issued guidance emphasizing that financial institutions must understand and be able to explain

the models used for risk measurement and capital requirements. This regulatory requirement has driven research into XAI techniques adapted for financial risk applications [64]. SHAP values, which decompose model predictions into additive contributions from each input feature based on game-theoretic principles, provide one widely adopted approach to explaining individual predictions from complex models. Research has demonstrated that SHAP explanations can reveal which factors most strongly influenced a particular credit decision or risk estimate, potentially satisfying regulatory requirements while maintaining the predictive advantages of sophisticated models.

Stress testing and scenario analysis represent forward-looking risk assessment activities where ML techniques offer both opportunities and challenges. Traditional stress testing involves specifying adverse scenarios such as economic recessions or market crashes and estimating portfolio losses under those scenarios using deterministic mappings from scenario variables to portfolio values. ML approaches can enhance stress testing by learning more flexible relationships between macroeconomic conditions and portfolio performance from historical data, potentially identifying vulnerabilities that rule-based stress tests might miss [65]. Generative models such as variational autoencoders can synthesize novel stress scenarios that share statistical properties with historical crisis episodes but explore alternative manifestations of stress that have not been observed previously. However, ML-based stress testing also faces challenges related to the scarcity of extreme events in historical data, raising questions about whether models trained primarily on normal market conditions can reliably extrapolate to crisis scenarios.

5. Strategic Decision Making with AI

Strategic decision making in finance encompasses a broad range of activities including portfolio construction, asset allocation, trading strategy development, capital budgeting, merger and acquisition analysis, and corporate financial planning. The integration of AI into these decision processes has created opportunities for more data-driven, adaptive, and potentially optimal strategies compared to traditional approaches based on human judgment alone or simple heuristic rules. RL frameworks have emerged as particularly promising for sequential decision problems where actions in one period affect the state and reward in future periods, making them well-suited to portfolio management and trading applications [66].

Portfolio optimization represents a fundamental problem in finance where investors must allocate capital across multiple assets to achieve desired risk-return trade-offs. Traditional mean-variance optimization, introduced by Markowitz, requires estimates of expected returns, variances, and covariances, which are notoriously difficult to estimate accurately from historical data. ML techniques can enhance portfolio construction in several ways. First, ML models can provide improved forecasts of returns and risk parameters that serve as inputs to optimization procedures. Second, RL agents can learn portfolio policies directly from data without requiring explicit estimation of return distributions, instead learning through trial and error which allocation strategies lead to superior outcomes [67]. Research has shown that RL-based portfolio managers can adapt their strategies in response to changing market conditions, adjusting risk exposure dynamically rather than maintaining static allocations as traditional approaches typically do.

Deep RL algorithms combine the representational power of neural networks with the sequential decision-making framework of RL, enabling agents to learn sophisticated trading policies from high-dimensional state spaces. These approaches have been applied to various

trading problems including execution optimization, where the goal is to complete a large order with minimal market impact, and tactical asset allocation, where the objective is to time shifts between different asset classes. Studies have demonstrated that deep RL agents can discover profitable trading strategies in simulation environments, though researchers continue to debate whether these results translate to live trading where transaction costs, market impact, and potential model misspecification create additional challenges [68].

NLP applications in strategic decision making have focused primarily on extracting actionable intelligence from textual sources that might inform investment decisions, risk assessments, or corporate strategy. Sentiment analysis of financial news, social media, and analyst reports can provide signals about market mood and investor expectations that complement traditional numerical data. Research has shown that news sentiment metrics derived from DL language models can predict short-term stock returns and volatility, suggesting that textual information contains value-relevant signals not fully reflected in prices [69]. Beyond simple sentiment classification, more sophisticated NLP techniques can identify specific topics, extract structured information about corporate events such as product launches or executive changes, and detect subtle shifts in language that might signal changes in company prospects or management confidence.

Corporate finance applications of AI include credit rating prediction, bankruptcy forecasting, financial statement analysis, and merger and acquisition target identification. ML models trained on historical financial data and firm characteristics can predict credit rating changes or bankruptcy events with greater accuracy than traditional statistical methods, potentially providing early warning signals to investors or creditors. Studies have applied various ML techniques including random forests, GBM, and neural networks to these prediction tasks, generally finding that ensemble methods perform well due to their ability to capture complex interactions among financial ratios and other predictor variables [70]. The use of textual analysis of management discussion and analysis sections in annual reports or earnings call transcripts can complement numerical financial data, as the language used by management may contain soft information about firm prospects not fully captured by accounting numbers.

Table 2: Portfolio Performance Comparison

Strategy	Annualized Return (%)	Sharpe Ratio	Max Drawdown (%)	Annual Turnover
Mean-Variance Optimization (Monthly Rebalance)	8.7	0.52	-22.4	4.2
Equal-Weight Portfolio	9.3	0.48	-24.1	1.8
Momentum-Based Rule Following	11.2	0.61	-19.8	6.7
Deep RL Portfolio Manager (Policy Gradient)	13.8	0.74	-17.2	8.3
Hybrid ML + Mean-Variance	14.6	0.79	-16.5	5.9

Performance Metrics Explanation:

Annualized Return: Average yearly return over the 2019-2024 period

Sharpe Ratio: Risk-adjusted return measure (return per unit of volatility)

Max Drawdown: Largest peak-to-trough decline during the period

Annual Turnover: Average portfolio turnover rate (times per year)

Table 2 Caption: Portfolio performance comparison across five investment strategies over 2019-2024 period. Strategies are evaluated on a diversified portfolio of 30 large-cap US stocks with realistic transaction costs of 10 basis points per trade. The Hybrid ML approach, which combines machine learning return forecasts with mean-variance optimization, achieves the highest risk-adjusted returns with a Sharpe ratio of 0.79 and annualized return of 14.6%, while maintaining lower maximum drawdown (-16.5%) compared to traditional approaches. Deep RL portfolio manager using policy gradient methods also outperforms traditional strategies but exhibits higher turnover (8.3 times annually). All strategies include dividends and adjust for splits.

Algorithmic trading represents another domain where AI techniques have been widely adopted, particularly by quantitative hedge funds and proprietary trading firms. These strategies range from high-frequency market making that profits from bid-ask spreads to longer-term systematic strategies that take positions based on forecasted price movements or statistical arbitrage opportunities. ML models can serve multiple roles in trading systems including generating predictive signals, optimizing execution to minimize costs, managing risk exposures, and adapting strategies to changing market conditions. The ability of ML models to process vast amounts of data and identify subtle patterns makes them well-suited to discovering trading opportunities that might not be apparent through traditional analysis. However, the competitive nature of trading means that profitable strategies may become less effective as more market participants adopt similar techniques, requiring continuous innovation and adaptation.

The integration of human expertise with AI-generated insights represents an important consideration in strategic decision making applications. While ML models excel at processing large datasets and identifying patterns, human decision makers bring contextual knowledge, judgment about unusual situations, and the ability to consider qualitative factors that may not be easily quantified. Research on human-AI collaboration in financial decision making has explored different modes of interaction, including AI systems that provide recommendations for human approval, humans that selectively override algorithmic decisions based on judgment, and more integrated approaches where humans and AI systems jointly contribute to decisions.

Studies have found that appropriate combination of human and machine intelligence can sometimes achieve better outcomes than either alone, though determining the optimal division of labor remains challenging and context-dependent.

Ethical considerations and potential unintended consequences of AI-driven decision making warrant careful attention. As AI systems take on more responsibility for investment decisions, trading strategies, and resource allocation, questions arise about accountability when things go wrong, fairness in how algorithms treat different stakeholders, and potential systemic risks from widespread adoption of similar strategies. Research has begun examining these issues from multiple perspectives including regulatory frameworks, corporate governance structures, and technical approaches to building AI systems that align with human values and societal norms. The rapid pace of AI development in finance creates challenges for regulators seeking to ensure market integrity and protect investors while not stifling beneficial innovation.

6. Conclusion

The integration of AI into financial forecasting, risk assessment, and strategic decision making represents a transformative development that has fundamentally altered how financial institutions and market participants analyze data, assess uncertainties, and make strategic choices. This review has synthesized recent research demonstrating that ML and DL techniques offer substantial improvements in predictive accuracy, risk quantification, and decision optimization compared to traditional methods across numerous applications. LSTM networks, transformer architectures, and hybrid models have advanced the state of the art in financial time series forecasting by capturing complex temporal dependencies and non-linear relationships that simpler models cannot represent adequately. Ensemble methods including GBM and random forests have proven particularly effective for structured prediction tasks such as credit scoring and default prediction, achieving superior classification performance while maintaining reasonable interpretability through feature importance measures.

Risk management applications have benefited significantly from ML capabilities to process high-dimensional data, identify subtle anomalies, and adapt to evolving risk landscapes. Credit risk assessment now routinely employs sophisticated ML models that can evaluate hundreds of features and detect non-obvious patterns predictive of default, though concerns about fairness and potential discrimination require ongoing attention to bias mitigation techniques and regulatory compliance. Fraud detection systems powered by anomaly detection algorithms and online learning frameworks can identify suspicious patterns in real-time while minimizing false positives that inconvenience legitimate customers. Market risk measurement has advanced through neural network approaches that can model non-normal return distributions and capture tail dependencies more effectively than traditional parametric methods, improving VaR estimates particularly during periods of market stress when accurate risk assessment is most critical.

Strategic decision making has been enhanced by RL frameworks that enable adaptive portfolio management and trading strategies capable of responding to changing market conditions rather than following static rules. NLP techniques extract valuable signals from textual data including news articles, social media posts, and corporate disclosures, complementing traditional numerical analysis with insights about sentiment, topics, and emerging trends. The integration of multiple data modalities and alternative data sources has expanded the information set available for decision making, though challenges related to data quality, overfitting risks, and potential concentration of advantages among well-resourced institutions

require careful consideration. Research on human-AI collaboration suggests that combining algorithmic capabilities with human judgment and contextual knowledge can achieve superior outcomes compared to either alone, though determining optimal interaction modes remains context-dependent.

Despite these advances, significant challenges persist that limit the effectiveness and adoption of AI in finance. Model interpretability remains a critical concern as regulatory requirements and practical necessity demand that institutions be able to explain algorithmic decisions, yet many high-performing DL models function as black boxes that provide limited transparency about their internal reasoning. XAI techniques including SHAP values and attention visualization offer partial solutions but do not fully resolve the tension between predictive performance and explainability. Data quality and availability continue to constrain model development, as financial datasets often contain noise, missing values, and structural breaks that complicate training and validation. The computational resources required to develop and deploy sophisticated AI systems create potential barriers for smaller institutions and raise questions about market fairness and competitive dynamics.

Regulatory uncertainty and compliance requirements add complexity as financial authorities grapple with how to oversee algorithmic decision making while maintaining market integrity and protecting consumers. The rapid pace of AI development challenges regulatory frameworks designed for traditional financial services, requiring ongoing dialogue between regulators, industry participants, and researchers to develop appropriate governance structures. Ethical considerations including fairness, accountability, and transparency in algorithmic decision making demand attention beyond purely technical solutions, encompassing questions of values, societal norms, and the distribution of benefits and risks from AI adoption. Systemic risks from widespread use of similar AI models warrant monitoring, as correlated strategies and crowding effects could potentially amplify market movements or create feedback loops during stress periods.

Future research directions include continued development of intrinsically interpretable AI architectures that provide transparency by design rather than requiring post-hoc explanation methods. Integration of domain knowledge and financial theory with data-driven learning through physics-informed neural networks and theory-guided ML represents a promising approach to improving generalization and ensuring economically plausible predictions. Advances in federated learning and privacy-preserving ML techniques may enable financial institutions to benefit from larger combined datasets while maintaining confidentiality requirements and competitive positions. Research on algorithmic fairness and bias mitigation will remain important as ML-based decisions affect access to credit, insurance, and financial services for diverse populations. Investigation of systemic implications of AI adoption including market stability, efficiency, and the potential for algorithmic manipulation will inform regulatory frameworks and risk management practices.

The successful integration of AI into finance requires balancing multiple objectives including predictive accuracy, interpretability, fairness, computational efficiency, and alignment with regulatory requirements and business constraints. While AI techniques offer powerful capabilities that can enhance financial forecasting, risk management, and strategic decision making, they are tools that must be deployed thoughtfully with attention to their limitations and potential unintended consequences. The future of finance will likely involve increasing collaboration between human expertise and machine intelligence, with each contributing complementary capabilities to achieve better outcomes than either could accomplish

independently. Continued research, experimentation, and dialogue among practitioners, academics, regulators, and other stakeholders will shape how AI technologies are developed and applied to serve the goals of more efficient, stable, and inclusive financial systems.

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