

# *Innovative Developments and Risk Challenges of Artificial Intelligence Model in Quantitative Finance for Investment*

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**Abstract.** Artificial intelligence (AI) has become crucial in quantitative finance, driving improvements in investment modeling, strategy development, and risk assessment. This paper reviews recent advancements in AI-enhanced quantitative investing, emphasizing deep learning, reinforcement learning, and algorithmic optimization. Research by Ding and Qin achieved over 97% accuracy in stock predictions using Long Short-Term Memory (LSTM) networks, while Zhang's XGBoost framework improved high-frequency trading performance, yielding a mean squared error (MSE) of 0.1918. Xu et al. implemented a Kalman Filter-based PI clock servo, achieving nanosecond-level synchronization precision (59.37 ns) in multi-hop networks, enhancing scalability. In financial risk forecasting, Duan et al. increased K-Means clustering accuracy to 99.4%, reducing false alarm rates by nearly 48%. Additionally, optimization techniques like PPO, CVaR-based risk management, and quantum optimization have improved stability, risk control, and computational efficiency. However, challenges like data diversity, model interpretability, and regulatory oversight persist. In conclusion, integrating AI into quantitative finance enhances predictive accuracy and decision-making, transforming intelligent asset management amid changing risk landscapes.

**Keywords:** Quantitative Finance, Artificial Intelligence, Risk Management

## **1. Introduction**

Artificial Intelligence (AI), a branch of computer science, has the capability to make decisions across various domains, including finance, healthcare, and business, by emulating human thought processes. In recent decades, AI has advanced rapidly, evolving into a general-purpose technology that is being adopted across numerous sectors. The stock market, often linked with deep learning, represents a subfield of AI. Deep learning is one of the AI models that involves machine learning algorithms that utilize multilayer neural networks, enabling them to classify and recognize patterns directly from raw data without the need for task-specific prior knowledge. In equity investment, text processing can leverage deep learning's capabilities to mine information from news articles, microblogs, and forum discussions. This approach can provide valuable insights by integrating both numerical and textual data to develop quantifiable sentiment indicators.

In stock market modeling, several techniques are commonly utilized, including the Linear Regression (LR) model, tree-based models, and Long Short-Term Memory (LSTM) models. Ding

proposed an extended structure of a deep recurrent neural network based on LSTM, namely the multi-valued associated neural network model (Associated Net), was proposed, which realizes the end-to-end joint prediction of multiple related outputs [1]. In this research, they applied the total loss function as the overall optimization objective, optimized the Adam algorithm execution, and used the MSE and MAE as the evaluation standard. What's more, they also cited the Dropout probability mechanism [1]. As a result, the average accuracy of the Shanghai Index is 95.6%–97.4%. 98.6% (open), 97.9%(low),98.2%(high)for PetroChina and 96% for ZTE [1]. Yifan Zhang raised a stock price prediction model combining the XGBoost algorithm and the Grid SearchCV parameter optimization mechanism. The research focused on the temporal characteristics of stock daily data and constructed a machine learning prediction framework capable of accurately capturing the high-frequency fluctuation trends, and used the XGBoost gradient boosting tree algorithm serves as the core of the modeling process [1]. Finally, the validation score is -0.431, and the MSE is 0.1918 [1]. This method has a higher prediction accuracy than traditional methods, and the fitting degree has significantly improved [1].

Drawing on research conducted both globally, this article provides an overview of the application scenarios and current research status of AI models in the investment sector. It examines the future development of AI technology within the financial industry from four key perspectives: investment information acquisition, stock price prediction, enhancement of investment strategies, and optimization of trading systems. Additionally, the article addresses the challenges and risks that AI models encounter in investment applications. This paper focuses on emerging AI trends and the associated risk issues within the asset management sector of the financial industry.

## 2. Current application status of AI in financial industry

Artificial intelligence (AI) significantly impacts finance, particularly through quantitative trading, which utilizes advanced statistical methods and algorithms to analyze extensive historical transaction data. This approach helps traders identify key factors influencing market dynamics, like transaction timing and quantity variations in response to price changes, leading to stable and profitable outcomes. The origins of quantitative trading date back to the early 1980s, developing foundational concepts that evolved into algorithmic trading by the late 1990s [2]. As algorithms were refined using large datasets, traders began to adopt AI technologies. Today, AI enhances quantitative trading in crucial areas such as stock price prediction, factor mining, and anomaly detection, further improving the effectiveness of trading strategies and revolutionizing market engagement.

The primary aim of quantitative trading is to automate trading strategies through sophisticated computer programs. This automation leads to rapid trade execution, minimizes human error, and allows traders to seize market opportunities more efficiently [2]. As technology progresses, the fusion of AI and finance is expected to create innovative solutions that will reshape quantitative trading, empowering investors to navigate complex financial markets confidently.

Brownian motion is a stochastic process and numerical method that is commonly used in the field of quantitative finance. It plays a significant role in areas such as stock prices, option pricing, risk management, fixed income, and stochastic volatility. In 2012, James P. McNichols and Joseph L. Rizzo established a mathematical model based on random geometric Brownian motion to simulate and predict the price fluctuations of financial markets, including foreign exchange, commodity prices, stock indices, and other market assets, in order to support the economic capital calculation and risk management of insurance companies and financial institutions [3]. They applied the GBM to establish the model of asset price as their core method and used it to simulate the time

series of the real market. At the same time, they also cite the CIR model to show the process of the short-term interest rate. Then they used modular economic capital estimation [3]. For the model experiment, the research took the foreign exchange market of GBP/USD as an example, and used the option forward curve and implied volatility data from June 2010 to December 2011 (from Bloomberg source) for simulation. Consequently, the research showed that the actual currency price trends fluctuate within the 95% confidence interval of the model [3]. The prediction intervals demonstrated good coverage and validity. This research had many advantages categories such as market-consistent, mathematical rigor and interpretability, risk quantifiability, and so on. For the market-consistent, the model inputs were directly derived from the option forward curve and the implied volatility, perfectly aligning with the expectations of the real market and achieving the "no-arbitrage" assumption. For the risk quantifiability, it presented the distribution pattern of the prices directly, along with the capital risk levels under each confidence interval. This improved GBM-CIR framework maintains theoretical rigor while achieving high operability and market accuracy, and has become an efficient tool for economic capital assessment and risk spread calculation in insurance and financial institutions.

Attila Ceffer and Janos Levendovszky proposed a new algorithmic framework based on quantitative and volatility information to estimate the forward conditional probability distribution, aiming to address the core challenge of high-frequency electronic trading - how to accurately predict price changes and generate trading signals within an extremely short period of time [4]. They used FOREX as the experiment environment and applied FCPF Estimation as the core of the trade strategy. The processes are quantified the asset return sequence  $r(t)$  discretely, a feedforward neural network (Feedforward Neural Network, FFNN) was used to learn the mapping relationship between the historical return sequence and the distribution of next-period return conditions and the learned FCPD was utilized to trigger buy or sell signals under given thresholds  $\varepsilon$  and  $\eta$ ; during the execution phase, by filtering out high-volatility periods and optimizing parameters adaptively, the trading accuracy and stability of returns were improved [4]. According to the data of EUR/USD, GBP/USD, and NZD/USD retrieved from FOREX, they comprehensively applied FCPD prediction, Lloyd–Max quantization, volatility signal filtering, and simulated annealing optimization, an intelligent trading algorithm system that can achieve high-frequency trading (HFT) and was empirically effective has been proposed. The model achieved a price direction prediction accuracy rate of approximately 70–80% at the distribution prediction level; in the real-time EUR/USD data, the daily net profit reached 5.3%–6%, and the maximum drawdown was less than 1.5%; through quantitative and volatility filtering, the computational complexity was significantly reduced, providing a theoretical basis for real-time trading and low-latency algorithms. This research not only provided a new approach in theory for trading decisions based on probability distributions, but also demonstrated in the field of high-frequency financial intelligent algorithms an outstanding model that combines high feasibility, high accuracy, and strong robustness.

Emotions and Alternative Data for Early Risk Warning is a branch within the field of risk control and infrastructure in quantitative finance. In 2022, Xiaoli Duan, Xuexia Du, and Limei Guo, regarding the issue of financial risk warning for digital industry enterprises, the authors had proposed an intelligent warning system based on the improved K-Means clustering algorithm, which was designed to address the challenges of risk identification posed by complex, multi-source, and high-frequency data in the context of the digital economy [5]. This research addressed the issues of slow operation, redundant dimensions, and noise interference in traditional risk warning models through improving the K-Means algorithm, and constructed a digital industry financial risk warning system, forming a dual-layer innovation model of "algorithm + system platform". They optimized

the algorithms on algorithm optimization, automatic selection of subspaces, dynamic update mechanism, and a multi-agent system [5]. For the data and evaluation methods, they used a large scale of data, preprocessing of missing values, task specification, and so on. Consequently, the precision accuracy was better than the previous one. The prediction accuracy of the improved K-Means algorithm had been increased by approximately 1% - 2%, reaching 99.4%. The sensitivity (0.652) was more than 1.8 times the average value of other algorithms (about 0.35), indicating that it had a lower false alarm rate and fewer missed detections when capturing risk signals; the cost of incorrect classification had decreased by approximately 48% (from 8 thousand to 4 thousand), significantly enhancing its economic practicability [5]. By using the K-means algorithm, the accuracy rate of the early warning can reach as high as 97% or more, and remains stable based on the study on more than 100 listed digital industry enterprises [5]. Improving the K-Means algorithm not only significantly outperformed traditional clustering methods in terms of accuracy but also boasted faster computing speed and stronger feature adaptability. It could be used as a high-performance core algorithm for real-time financial risk warning in the digital industry. This research provided a new theoretical approach and practical paradigm for real-time early warning systems based on intelligent algorithms in the field of fintech.

Time synchronization has a huge impact on quantization. Xu proposed a new time synchronization method to reduce the cumulative impact of timestamp quantization errors on the synchronization accuracy of multi-hop networks, and achieved a high-precision and low-cost distributed clock synchronization mechanism [5]. The research team proposed and verified a PI clock servo mechanism based on Kalman filtering, which is used to reduce the cumulative growth rate of quantization errors in multi-layer node networks. As for the innovation, the team combined the PI clock servo with Kalman state estimation to construct a state space model that included clock deviation and frequency drift, and then filtered out the timestamp noise caused by quantization online [6]. Finally, under the four-hop network, the maximum clock deviation was only 59.37 ns; the growth rate of synchronization error had significantly decreased, and the error increased linearly with the hop count, no longer accumulating exponentially; the synchronization performance could be comparable to the current most advanced IEEE 1588-2008 synchronization scheme, but it only used low-cost crystal oscillators instead of expensive TCXO/OCXO; it had proved that Kalman fusion control could effectively filter out quantization errors and improve system scalability [6]. This achievement has broken through the physical limitation of low-cost clock synchronization and has verified that the multi-node synchronization control based on filtering compensation can achieve industrial-grade nanosecond accuracy without increasing the hardware cost. It has significant implications for future large-scale real-time control and distributed intelligent systems.

### 3. Advantages of quantitative finance

In the field of financial asset allocation, the selection of the rolling window is crucial for optimizing the investment portfolio.

Anupam Prakash and Daniel Szilágyi completed research. This research focuses on the quantum algorithmic achievements for the constrained portfolio optimization problem [7]. Their target was constructing a quantum optimization algorithm that can be executed under constraints such as positive investment constraints, budget upper limit constraints, and so on, and demonstrated its significant acceleration performance over classical algorithms in terms of theoretical complexity and actual computation time. Their innovations in this research were transforming the investment portfolio optimization problem into an SOCP, constructing a quantum interior-point method to solve the SOCP, achieving simultaneous handling of positive constraints and budget constraints, and

implementing complexity reduction by using the HHL quantum linear system solver as the core operator. They fetched data from the cvxportfolio library, selected 50 enterprises, multiplied the prices for the previous 100 days, and imposed the limitation of the average rate of return and non-negative investment.

Duan et al. developed a new algorithm called OASS (Optimal Adaptive Step Size), treating financial transactions as sequential decision-making problems. They modeled the temporal correlations of environmental states using multi-layer long short-term memory networks and employed probabilistic dynamic programming to handle high noise and uncertainty, thus eliminating the need for complex reward function design. The proximal policy optimization algorithm (PPO), which has received significant attention in the academic community for its outstanding performance in stability and wide applicability, has also been widely applied in this field [8].

To avoid the asymmetric risks in financial quantitative trading, Alameer et al. were the first to introduce Conditional Value at Risk (CVaR) into the deep reinforcement learning framework, leveraging its convexity-preserving feature to ensure the mathematical convexity of the problem itself. However, in the processing of high-dimensional data, this method still has room for optimization [9]. By interacting with the environment through PPO and continuously updating the strategy parameters, this method achieves the goal of minimizing the risk of the investment portfolio.

An overview of the strategy-driven deep reinforcement learning techniques for financial quantitative trading including strategy gradient algorithms, LSTM networks, and PPO in the previous analysis. These techniques demonstrated strong performance on different tasks. However, certain methods which increased the ability to capture tail risk using the conditional value at risk, but also increased model complexity and were based on assumptions about future markets, so it was difficult to observe the market. Moreover, though PPO's steady update strategy is used to train large language models, its effectiveness in highly noisy and unpredictable financial markets requires further investigation.

## 4. Problems and challenges that AI faces in financial industry

### 4.1. Data challenge

For some, the financial field has its own set of specific set of data advantages that could include financial market data, organizational data, macroeconomic indices, and public opinion. But it is facing a number of obstacles. The types of data itself are extensive and often lack standardization; for example, financial market data is structured, while corporate financial data is largely unstructured, making it difficult to analyze. The quality of data may be problematic as missing, deviated, or erroneous data can have a big impact on AI model training and accuracy [2]. Missing data can prevent comprehensive feature extraction, while offsets and errors can lead to incorrect predictions. Additionally, while the volume of data is vast, much of it is unstructured and unsuitable for AI model training, necessitating conversion into structured formats for effective machine learning or deep learning applications.

### 4.2. Supervision issue

The rapid emergence of artificial intelligence in financial systems will surely have challenges for users. For example, in the area of financial investment advice AI analysis might tell people about various financial products, but it is possible that users will be given misinformation if AI systems

have a lack of accuracy. Thus there is a need to regulate artificial intelligence in the finance sector to make these systems capable of making fair and sound decisions, thus reinforcing the integrity of the entire financial industry. In addition to regulating the AI systems of that technology, it also is essential to regulate the use of the data. It is necessary to confirm that the use of the data is necessary, secure, and lawful. At present, some AI applications, particularly large models, offer personalized services which are given according to the previous behavior and the personal information of the user, which raises concerns about potential misuse of private information [2].

## 5. Conclusion

The evolution of artificial intelligence (AI) in the financial sector has been very much one of continuing improvement over this time. From rudimentary expert systems to sophisticated algorithmic models that better process data and extract conclusions, AI has developed over the years. The change from machine learning to deep learning is one of the significant landmarks that has widened the data span from simple to big data applications. More recently we have seen the integration of large-scale models at scale with finance, enabling intelligent agents, which can learn on their own and adapt their task management skills to meet a complex task. In this article, we emphasize the importance of quantitative finance in the current market, using quantitative model itself as a framework, followed by the applications of different quantitative model techniques. As per the recent literature, modern quantitative technologies greatly influence market trends. For financial institutions, insights into AI trends can help them with strategic planning—so they can optimize infrastructure, optimize resources, or protect valuable assets—thus improving competitiveness. Yet we cannot use quantitative finance models, the article states, but instead need to pull from the literature. Further research would aim to confirm these and lead to an elaboration of the dialogue concerning quantitative finance and the models therein.

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