Frontiers in Economics and Management Volume 7 Issue 1, 2026
ISSN: 2692-7608 DOI: 10.6981/FEM.202601_7(1).0019

Risk Management in AI-Based Quantitative Trading: A Comprehensive Review and Perspective

Xuanting Wu*

Weifang NO.1 Middle School, Weifang, Shandong, 261339, China

*xuantingpaulwucwss@cseec.education

Abstract

This paper offers an expanded review and perspective on risk management in artificial intelligence (AI)-based quantitative trading. As machine learning and deep learning approaches gain influence in financial markets, their reliability and adaptability under volatile conditions have become major concerns. This review follows a structured approach, beginning with a recall of the background and motivation for studying AI in quantitative finance. The main body integrates recall with viewpoints by reviewing literature, empirical studies, and case evidence, while adding critical perspectives on data dependence, overfitting, market instability, and systemic risk. Finally, the conclusion presents a viewpoint on how AI can be more effectively embedded into financial systems, highlighting the need for hybrid models, explainability, regulation, and robust oversight. This comprehensive treatment aims to contribute to academic debates while offering practical guidance to practitioners, regulators, and policymakers.

Keywords

Artificial Intelligence; Quantitative Trading; Risk Management; Financial Markets.

1. Introduction (Recall)

The integration of artificial intelligence (AI) into financial markets has revolutionized quantitative trading[1]. Unlike traditional statistical models, AI systems can learn complex nonlinear relationships, detect hidden patterns in large datasets, and adapt dynamically to changing market environments[2]. These capabilities have attracted hedge funds, asset managers, and institutional investors who seek higher returns and more efficient execution. However, this progress comes with significant risks. Historical crises-such as the Flash Crash of 2010, the 2008 financial crisis, and the market turbulence during the COVID-19 pandemic-illustrate how automated trading systems may exacerbate volatility instead of reducing it[3]. AI, while powerful, depends on the quality of input data, assumptions about historical patterns, and stability in financial infrastructures. When these assumptions break down, AI systems may fail catastrophically[1,3]. Thus, understanding and strengthening risk management in AI-based trading is an urgent priority for both academia and industry[2,4].

2. Representative Risks in AI-Based Quantitative Trading

2.1. Model Risk (Overfitting and Algorithmic Failure)

AI models, particularly deep learning systems, are prone to overfitting-capturing noise in historical data rather than true patterns[1,5]. This leads to poor generalization in live markets. Additionally, algorithmic failure may occur when models face structural breaks such as regime shifts or unexpected policy changes[3].Model risk also comes from the way models are updated. Many AI models are trained at fixed time intervals. If market conditions change quickly, the

ISSN: 2692-7608 DOI: 10.6981/FEM.202601_7(1).0019

model may still rely on outdated information. This delay increases the chance of wrong decisions.

2.2. Data Dependency and Quality Risk

AI systems depend heavily on large datasets. Incomplete, biased, or delayed data can mislead algorithms and trigger faulty decisions[2]. For example, sentiment analysis based on social media may amplify noise rather than provide reliable signals[1].Another problem is data consistency. Data from different sources may follow different standards. When these datasets are combined, errors may appear. Even small data mismatches can affect model outputs.Liquidity risk becomes more serious when markets move quickly. During sharp price changes, it may be difficult to execute trades at expected prices. This leads to higher losses than predicted by models.

2.3. Market Liquidity and Volatility Risk

AI-driven strategies may exacerbate market volatility, especially when many institutions use similar algorithms. Herding behavior can amplify liquidity shortages, leading to flash crashes or cascading sell-offs[3,4].

2.4. Operational and Cybersecurity Risk

Automated systems depend on technological infrastructure, which makes them vulnerable to system outages, latency, and cyberattacks[2,4]. An intrusion could manipulate input data or disrupt trading platforms, resulting in financial and reputational damage[4].

3. Main Body (Recall + Viewpoint)

3.1. Literature Review (Recall)

The literature on AI in finance can be divided into three strands. First, predictive modeling research shows that deep learning models such as LSTM, CNN, and reinforcement learning outperform traditional regression and econometric models in capturing complex signals[1,5]. Studies by Lopez de Prado (2018) and Zhang et al. (2021) highlight that AI can significantly improve portfolio optimization and asset allocation[1,5]. Second, risk management research emphasizes the fragility of AI models under stress. Chen et al. (2020), for instance, analyze algorithmic trading during COVID-19 and show how models trained in calm periods fail in turbulent markets[3]. Third, broader discussions in financial economics point to systemic risks, including herding effects, feedback loops, and liquidity crises amplified by automated decision-making[4]. These strands together illustrate that AI offers both opportunities and vulnerabilities.In addition, existing literature often focuses more on model performance than on long-term stability. Many studies test AI models using historical data under ideal conditions. However, real markets are more complex and uncertain. Factors such as transaction costs, liquidity limits, and sudden news shocks are not always fully considered.Another limitation in the literature is that different studies use different datasets and evaluation standards. This makes it difficult to compare results across papers. Some models appear strong in one study but weak in another. This suggests that AI performance is highly dependent on testing conditions. Therefore, conclusions from the literature should be interpreted with caution.

3.2. Critical Viewpoints

While existing research demonstrates AI's capabilities, critical viewpoints are necessary to contextualize these findings[2,4]. One limitation is overfitting: models that perform well on historical datasets often fail to generalize to new conditions[1]. Another concern is data dependency: if market sentiment shifts abruptly due to unforeseen geopolitical or health crises, AI systems lack the foresight to adapt[3]. A third issue is the opacity of deep learning. These

ISSN: 2692-7608 DOI: 10.6981/FEM.202601_7(1).0019

models act as black boxes, reducing interpretability and accountability, which raises regulatory and ethical concerns[2,4]. From a systemic perspective, if many institutions use similar AI strategies, synchronization risks can create cascading effects[4].From a practical perspective, risk often comes from the gap between model design and real trading behavior. Even a well-trained model may produce unstable results if it is used without proper supervision. Traders may also misunderstand model signals and apply them incorrectly.

3.3. Empirical Observations (Recall + Viewpoint)

Empirical evidence from stock indices, forex, and commodities markets reveals important insights[3,5]. In stable markets, LSTM and XGBoost deliver high predictive accuracy, low drawdowns, and strong Sharpe ratios above 1.5[1,5]. However, in moderately volatile conditions, model performance diverges. LSTM adapts well to trends but falters in sideways markets, while XGBoost captures short-term shifts but suffers from high variance[5]. In extreme cases such as the COVID-19 crash, both models recorded significant drawdowns, frequent stop-loss activations, and higher events[2,3].Another observation is that risk measures are sometimes ignored. Many evaluations focus mainly on returns. However, drawdowns and volatility are equally important. A strategy with high returns but large losses may not be suitable for long-term use. Therefore, empirical analysis should balance return and risk indicators.

3.4. Case Studies and Comparative Analysis

Case studies further illustrate both success and failure in AI trading[1,3]. During the 2020–2021 recovery phase, several hedge funds using hybrid AI-human strategies outperformed benchmarks, leveraging sentiment analysis of news and social media[5]. In contrast, fully automated models without risk control measures suffered heavy losses when volatility spiked after unexpected policy announcements[3]. Comparative analysis across regions also reveals differences: AI models trained on developed markets show stronger performance than those in emerging markets, where structural breaks and data quality issues reduce reliability[5]. In many failure cases, losses increased because models reacted too slowly to market changes. In contrast, successful cases often adjusted trading intensity based on market conditions.

Moreover, organizational structure plays a role in trading outcomes. Firms with clear risk responsibilities and communication channels are better able to control losses. This shows that AI performance is influenced not only by technology, but also by management practices.

4. Risk Management Recommendations

Effective risk management in AI-based quantitative trading requires a multi-layered defense strategy that integrates technical, operational, strategic, and regulatory dimensions[2,4]. At the technical level, robust model design, continuous stress testing, and strict data validation are essential to ensure reliability[5]. Operational measures should focus on cybersecurity, backup systems, and contingency planning to prevent disruptions[4]. Strategically, firms should diversify their models, combine human judgment with algorithmic decision-making, and maintain hybrid oversight mechanisms[1,5]. Finally, strong regulatory frameworks must promote transparency, monitor systemic risks, and encourage global coordination[2,4]. Together, these layers create a resilient foundation that balances innovation with stability in the rapidly evolving landscape of AI-driven finance[1-5].Risk management should also consider behavioral factors. Traders may place too much trust in AI systems and ignore warning signs. This overconfidence increases potential losses. Clear rules and regular reviews can help reduce this problem.

ISSN: 2692-7608 DOI: 10.6981/FEM.202601_7(1).0019

In addition, risk management tools should be tested under different scenarios. Stress testing helps identify weaknesses before real losses occur. Simple stress scenarios can already provide valuable information. Over time, this practice improves system reliability and confidence.

5. Conclusion (Viewpoint)

This comprehensive review underscores that AI-based quantitative trading is both promising and perilous. The recall of existing research and empirical studies shows that AI systems excel in stable environments but falter during crises. The viewpoints offered here emphasize three future directions. First, hybrid systems combining AI with human oversight and scenario-based stress testing are necessary to avoid catastrophic failures. Second, explainability and transparency must be prioritized to enhance accountability and trust. Third, regulators should establish guidelines that prevent systemic risks, such as herding effects and liquidity crises, while still encouraging innovation.

Looking ahead, the next generation of AI in finance should integrate diverse data sources, including alternative datasets such as satellite imagery, ESG indicators, and high-frequency sentiment. Such integration may improve generalization during unprecedented events. Furthermore, reinforcement learning methods that incorporate reward shaping based on risk metrics, not only returns, could enhance resilience. Finally, closer collaboration between academia, industry, and regulators will be essential to ensure that AI serves as a stabilizing force in financial markets rather than a destabilizing one.

References

[1] Lopez de Prado, M. (2018) Advances in Financial Machine Learning. Wiley, Hoboken, NJ, USA.

[2] Bartram, S.M., Branke, J., Motahari, M. (2020) Artificial Intelligence in Asset Management. J. Financ. Data Sci., 2(4): 1–18.

[3] Chen, Y., Fang, Y., Ma, L. (2020) COVID-19 and Algorithmic Trading. SSRN Electron. J., Preprint ID 3576830: 1–28.

[4] Arnott, R., Beck, N., Kalesnik, V. (2019) Alice's Adventures in Factorland. J. Portf. Manag., 45(7): 15–31.

[5] Zhang, Y., Yang, L., He, Z. (2021) Dynamic Portfolio Optimization with Deep Reinforcement Learning. Expert Syst. Appl., 178: 114–152.