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Risk management of quantitative trading systems based on the 4M1E framework and the Analytic Hierarchy Process

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Abstract. Against the backdrop of the accelerating development of the digital economy, quantitative trading systems face distinctive risks arising from their high degree of automation and structural complexity, rendering traditional information system risk management approaches inadequate. Grounded in the 4M1E framework, this study systematically identifies the sources of risk in quantitative trading systems across five dimensions—personnel, technology, data, methods, and external environment—and applies the Analytic Hierarchy Process (AHP) to quantitatively evaluate and rank the weights of these risk factors. The results indicate that external environment risks and methodological risks exert the most pronounced impact on system stability, with macro-market and extreme event risks, as well as the inconsistency between backtesting and live trading, receiving the highest weights. On this basis, the study proposes a closed-loop risk management strategy encompassing stress testing, model robustness validation, and the strengthening of compliance mechanisms, with the aim of enhancing the risk resilience of quantitative trading systems.

Keywords: quantitative trading, risk management, Analytic Hierarchy Process

1. Introduction

In recent years, the digital economy has continued to expand, and the integration of the digital and real economies has entered an accelerated phase. The Internet has evolved into a comprehensive space for information dissemination, sharing, communication, and collaboration, exerting a profound influence on industries across the real economy. In 2021, revenue from Internet data services reached RMB 25.83 billion, representing a year-on-year increase of 23.1% [1]. In 2023, the scale of China's digital economy was estimated at RMB 56.1 trillion, ranking second globally for several consecutive years, marking China as a major digital economy powerhouse. This trend is expected to further promote informatization and digital transformation across a wide range of industries [2]. Against this backdrop, financial trading methods are undergoing profound transformation. Traditional trading approaches, which largely relied on experiential judgment and manual operations, are gradually being replaced by quantitative investment methods centered on mathematical models, statistical analysis, and algorithmic execution. Through high-speed computation, automated execution, and real-time decision-making, quantitative trading integrates complex market data, investment strategies, and risk management mechanisms into a systematic process, thereby improving trading efficiency, strengthening strategy execution, and, to some extent, reducing subjective bias arising from human intervention. As a result, quantitative trading—representing the convergence of advanced information technology and financial trading—has experienced rapid global development in recent years.

In the field of quantitative trading, existing research has primarily focused on the design of trading strategies, model optimization, and algorithmic improvement. Specifically, extensive scholarly efforts have examined momentum strategies, mean reversion, machine-learning-based stock selection models, portfolio optimization, and backtesting frameworks [3]. Mojtaba et al. employed machine learning models such as decision trees, random forests, AdaBoost, and XGBoost to predict trends in the U.S. stock market over the past decade, concluding that deep learning approaches yield the most favorable results [4]. Fister et al. constructed a long- and short-term trend analysis system based on LSTM and validated it in the German market, finding that, compared with traditional strategies, their approach achieved superior performance for blue-chip stocks within a quantitative trading strategy based on full-market stock time series [5]. In addition, some studies have addressed the technical implementation of quantitative trading systems, including system architecture in high-frequency trading, execution latency control, and data processing platforms [6]. Jackie Shen identified nine major challenges facing modern programmatic trading and risk control, with particular emphasis on the development of automated control, testing, and simulation mechanisms [7]. However, most of these studies remain at the level of "strategy design" or "system implementation," focusing on improving returns, optimizing models, or reducing transaction costs, while relatively little attention has been paid to systemic risk management issues that arise when quantitative trading systems transition from research or experimental stages into real production environments.

Meanwhile, the field of information system risk management has developed a relatively mature body of research. Scholars have established rich theoretical frameworks and practical experience in areas such as information system security, business continuity, operational disruption, fraud prevention, system vulnerabilities, and data governance [8]. These studies are generally applicable to enterprise management systems, financial back-office systems, and cybersecurity systems, emphasizing process control, clear allocation of responsibilities, technical monitoring, and compliance review [9]. It should be noted, however, that although quantitative trading systems fall within the category of information systems, they possess distinctive characteristics: highly real-time operating environments, automated trading decisions, extremely agile signal–execution–feedback loops, and the potential for system failures to trigger substantial and instantaneous economic losses rather than mere IT operational interruptions. For these reasons, traditional information system risk management approaches are not fully applicable to quantitative trading systems, and their specific risks warrant dedicated investigation. In terms of risk identification, Addy W. A. argued that the integration of machine learning technologies into financial markets has fundamentally transformed traditional trading and risk management strategies, bringing unprecedented opportunities and challenges [10]. Regarding risk assessment, Bo Min, based on 189 interviews with market participants and field research at an algorithmic trading firm, suggested that the tightly coupled and highly complex interactions characteristic of automated trading make such systems prone to large-scale technical incidents [11]. With respect to risk response, Cristian Păuna emphasized that, in the design and implementation of automated trading systems within financial investment firms, capital and risk management solutions constitute the most critical component. Starting from the principle that trading systems must operate in a fully automated manner, corresponding system risk management strategies are essential to ensuring favorable expectations for algorithmic trading [12].

Against this background, this study approaches quantitative trading systems—an emerging and complex integration of technology and trading—from a risk management perspective. First, based on the 4M1E framework, the study constructs a risk identification structure for quantitative trading systems and systematically identifies risk sources across five dimensions: personnel, technology, data, methods, and the external environment. Second, the Analytic Hierarchy Process is employed to quantitatively evaluate different categories of risk factors. Through the construction of judgment matrices, weight calculation, and consistency testing, a scientific prioritization of risks is established. Finally, drawing on the empirical analysis results, the study conducts an in-depth discussion of key risk factors and proposes risk management measures tailored to the production-level operation of quantitative trading systems, thereby providing theoretical support and practical guidance for risk monitoring, priority-based resource allocation, and the stable operation of such systems.

2. Model and indicator system construction

2.1. Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making method that has been widely applied in decision analysis and risk assessment for complex systems. Its core idea is to decompose a complex problem into multiple hierarchical levels, ranging from the overall objective to criteria and then to specific alternatives or indicators, thereby forming a structured decision-making framework. AHP enables the transformation of qualitative judgments into quantitative analysis, making the decision-making process more systematic and transparent. In this study, AHP is employed to construct the risk indicator system for quantitative trading systems. By calculating the weights of various risk factors, the relative importance of each factor to overall system risk is determined, providing a basis for subsequent risk assessment and management.

2.2. Risk identification and construction of the evaluation hierarchical model

To scientifically identify potential risks in quantitative trading systems, this study is grounded in the 4M1E framework (Manpower, Machine, Material, Method, and Environment). In light of the structural characteristics and operational mechanisms of quantitative trading systems, risk sources are systematically identified and categorized across five dimensions: personnel, technology, data, methods, and the external environment. Through a comprehensive review of relevant domestic and international literature, an analysis of representative risk events, and a synthesis of industry practices, a risk identification system covering the entire lifecycle of quantitative trading systems is constructed. The specific structure of this system is illustrated in Figure 1.

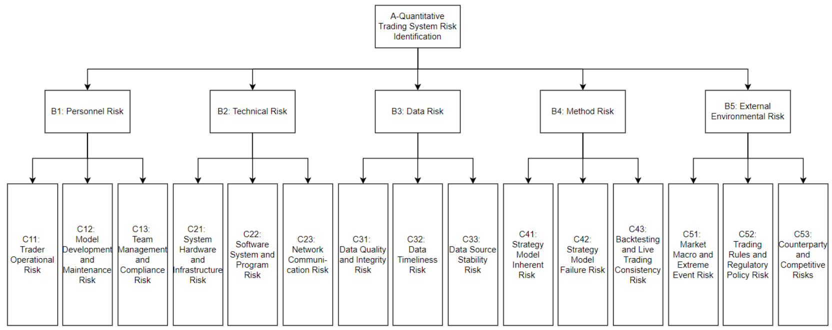

Figure 1. Risk identification framework for quantitative trading systems

2.3. Construction of the judgment matrix

The core of the Analytic Hierarchy Process lies in the construction of a scientific and rational judgment matrix. The judgment matrix reflects the relative importance between factors, and its accuracy directly affects the reliability of the resulting weights. In this study, multiple experts were invited to conduct pairwise comparisons of risk factors, and the average of the experts' scores was adopted as the value of each element in the judgment matrix, thereby reducing bias arising from individual subjective judgments.

In AHP, the 1–9 scale method is commonly used to express the relative importance between factors. The specific meanings of the scale values are shown in Table 1.

Table 1. The 1–9 scale method

Scale	Description
1	The two factors are of equal importance
3	The former factor is slightly more important than the latter
5	The former factor is clearly more important than the latter
7	The former factor is strongly more important than the latter
9	The former factor is extremely more important than the latter
2, 4, 6, 8	Intermediate values between two adjacent judgments
Reciprocal	If factor A is assigned a value of X relative to factor B, then factor B is assigned 1/X relative to factor A

Based on the above scaling rules, judgment matrices for the criterion layer and the indicator layer are constructed. After the judgment matrices are established, their maximum eigenvalue (λmax) and the corresponding eigenvector W are calculated. The eigenvector is then normalized to obtain the weights of the respective risk factors. To ensure the scientific validity and internal consistency of the results, consistency testing of the judgment matrices is required. The relevant formulas are as follows:

$$CI = (\lambda max - n)/(n - 1) \tag{1}$$

$$CR = CI/RI \tag{2}$$

where λmax denotes the maximum eigenvalue of the judgment matrix, n represents the order of the matrix, and RI is the average random consistency index corresponding to n. If CR < 0.1, the judgment matrix is considered to have acceptable consistency; if CR > 0.1, the matrix must be adjusted to improve its consistency.

3. Empirical analysis

3.1. Data analysis and consistency testing

To determine the relative importance of indicators at each hierarchical level, this study invited multiple experts in quantitative trading and risk management to conduct pairwise comparisons of the relevant factors. The average of the experts' scores was adopted as the final input for the judgment matrices. Subsequently, Python was used to process and compute the judgment matrices, deriving the eigenvectors and maximum eigenvalues for each level in order to determine the corresponding weights and perform consistency tests. The results indicate that the Consistency Ratios (CR) of all judgment matrices are below 0.1, satisfying the consistency requirement. This demonstrates that the expert evaluations exhibit a high degree of logical consistency and rationality, and that the calculated weights are reliable and valid. The specific results are presented in Table 2. Accordingly, the weights obtained at each level can be used as the basis for subsequent construction of the risk evaluation model, with the resulting evaluation matrices shown in Tables 3–8.

Table 2. Consistency test results

Level	Dimension	CI	RI	CR	Consistency
B	5	0.0162	1.12	0.01445	Passed
B1	3	0.0027	0.58	0.0046	Passed
B2	3	0.0043	0.58	0.0074	Passed
B3	3	0.0090	0.58	0.0156	Passed
B4	3	0.0051	0.58	0.0088	Passed
B5	3	0.0001	0.58	0.0002	Passed

Table 3. Evaluation matrix of the criterion layer (B)

	B1 Personnel Risk	B2 Technical Risk	B3 Data Risk	B4 Method Risk	B5 External Environment Risk
B1 Personnel Risk	1	1.1772	1.4579	0.5244	0.8217
B2 Technical Risk	0.8494	1	0.8640	0.8288	0.5098
B3 Data Risk	0.6859	1.1574	1	0.5793	0.5589
B4 Method Risk	1.9071	1.2065	1.7263	1	0.8398
B5 External Environment Risk	1.2170	1.9614	1.7891	1.1907	1

Table 4. Judgment matrix for B1: personnel risk

	C11 Trader Operational Risk	C12 Model Development and Maintenance Risk	C13 Team Management and Compliance Risk
C11 Trader Operational Risk	1	0.6565	0.5755
C12 Model Development and Maintenance Risk	1.5232	1	1.0905
C13 Team Management and Compliance Risk	1.7377	0.9170	1

Table 5. Judgment matrix for B2: technical risk

	C21 System Hardware and Infrastructure Risk	C22 Software System and Program Risk	C23 Network Communication Risk
C21 System Hardware and Infrastructure Risk	1	0.8159	0.5497
C22 Software System and Program Risk	1.2256	1	0.8898
C23 Network Communication Risk	1.8193	1.1239	1

Table 6. Judgment matrix for B3: data risk

	C31 Data Quality and Integrity Risk	C32 Data Timeliness Risk	C33 Data Source Stability Risk
C31 Data Quality and Integrity Risk	1	1.6208	1.0374
C32 Data Timeliness Risk	0.6170	1	0.9576
C33 Data Source Stability Risk	0.9639	1.0443	1

Table 7. Judgment matrix for B4: method risk

	C41 Intrinsic Strategy Model Risk	C42 Strategy Model Failure Risk	C43 Consistency Risk between Backtesting and Live Trading
C41 Intrinsic Strategy Model Risk	1	1.4103	0.6049
C42 Strategy Model Failure Risk	0.7091	1	0.5809
C43 Consistency Risk between Backtesting and Live Trading	1.6531	1.7216	1

Table 8. Judgment matrix for B5: external environment risk

	C51 Macro-Market and Extreme Event Risk	C52 Trading Rules and Regulatory Policy Risk	C53 Counterparty and Competitive Risk
C51 Macro-Market and Extreme Event Risk	1	1.5504	2.0437
C52 Trading Rules and Regulatory Policy Risk	0.6450	1	1.2615
C53 Counterparty and Competitive Risk	0.4893	0.7927	1

3.2. Risk assessment results

Based on the previously constructed Analytic Hierarchy Process model, the expert evaluation scores were incorporated into the assessment framework to compute the weights of risk indicators at each hierarchical level of the quantitative trading system. The resulting weight distribution of the various risk categories and their corresponding risk factors is summarized in Table 9. These results reveal the relative importance of different risk factors within the overall risk structure.

Table 9. Summary of weight calculation results for risk categories and associated risk factors

Target Layer (A)	Criterion Layer (B)		Indicator Layer (C)		Overall Weight
	Risk Categories	Weight	Risk Factors	Weight	
A Quantitative Trading System Risk Assessment	B1 Personnel Risk	0.1833	C11 Trader Operational Risk	0.2351	0.0431
			C12 Model Development and Maintenance Risk	0.3851	0.0706
			C13 Team Management and Compliance Risk	0.3798	0.0696
	B2 Technical Risk	0.1538	C21 System Hardware and Infrastructure Risk	0.2498	0.0384
			C22 Software System and Program Risk	0.3359	0.0517
			C23 Network Communication Risk	0.4142	0.0637
	B3 Data Risk	0.1469	C31 Data Quality and Integrity Risk	0.3924	0.0577
			C32 Data Timeliness Risk	0.2769	0.0407
			C33 Data Source Stability Risk	0.3307	0.0486
	B4 Method Risk	0.2492	C41 Intrinsic Strategy Model Risk	0.3050	0.0760
			C42 Strategy Model Failure Risk	0.2393	0.0596
			C43 Consistency Risk between Backtesting and Live Trading	0.4557	0.1136
	B5 External Environment Risk	0.2668	C51 Macro-Market and Extreme Event Risk	0.4690	0.1251
			C52 Trading Rules and Regulatory Policy Risk	0.2981	0.0795
			C53 Counterparty and Competitive Risk	0.2329	0.0621

At the criterion level, external environment risk (B5) exhibits the highest weight (0.2668), followed by method risk (B4) at 0.2492. Together, these two categories account for more than 50% of the total weight. This indicates that, from the experts' perspective, the robustness of trading models and strategies, as well as the external market and regulatory environment, constitute the primary sources of risk affecting the stable operation of quantitative trading systems. Personnel risk (B1) ranks third with a weight of 0.1833, suggesting that despite the high degree of automation in quantitative trading, human factors related to operation, management, and compliance continue to exert a significant influence on system security. By contrast, technical risk (B2) and data risk (B3) carry relatively lower weights; nevertheless, as fundamental components supporting system operation, their risk management remains essential and cannot be overlooked.

At the indicator level, the top five risk factors by overall weight are, in descending order: C51 macro-market and extreme event risk (0.1251), C43 consistency risk between backtesting and live trading (0.1136), C52 trading rules and regulatory policy risk (0.0795), C41 intrinsic strategy model risk (0.0760), and C13 team management and compliance risk (0.0696). These high-weight risk factors collectively highlight the vulnerabilities of quantitative trading systems with respect to strategy stability and external environmental changes, providing clear priorities for subsequent risk monitoring and resource allocation. The findings suggest that particular attention should be paid to the compounded effects of model failure and external shocks, and that enhanced robustness testing of trading strategies and improved mechanisms for responding to policy and regulatory changes are critical for strengthening the overall risk resilience of quantitative trading systems.

4. Discussion

4.1. Analysis of risk factors in quantitative trading systems

Based on the comprehensive evaluation results, this study finds that the overall risk of quantitative trading systems is primarily concentrated in two dimensions: the external environment and strategic methods, both of which occupy a dominant share of the total weight. In particular, macro-market and extreme event risk ranks highest, highlighting the system's pronounced sensitivity to external economic fluctuations and sudden shocks. Reversals in macroeconomic cycles, geopolitical conflicts, abrupt declines in market liquidity, or unexpected "black swan" events may all distort model inputs and invalidate predictive mechanisms, ultimately leading to systematic trading errors and substantial financial losses. At the same time, consistency risk between backtesting and live trading, as well as intrinsic strategy model risk, also warrant close attention. These risks reflect potential deficiencies in the model construction and validation stages, such as insufficient representativeness of backtesting samples, parameter overfitting, or the neglect of transaction costs. Such biases often result in significant deviations between live trading performance and theoretical expectations. Furthermore, policy adjustments, tightening regulatory oversight, or changes in exchange rules may directly disrupt strategy logic and capital allocation processes. Overall, once these key risks overlap or are triggered simultaneously, they may lead to trading execution interruptions, sharp fluctuations in returns, strategic misjudgments, or compliance failures, thereby posing systemic threats to the continuous operation of quantitative trading systems and the stability of institutions.

A substantial body of domestic and international research has similarly noted that quantitative trading systems or algorithmic trading strategies are prone to concentrated outbreaks of systemic risk when confronted with rapidly changing market environments, flawed internal model assumptions, or failures in technical controls. Min B. H. pointed out that the characteristics of "tight coupling" and "highly complex interactions" inherent in automated trading systems endow them with the potential for accident-like failures when exposed to market shocks [11]. In addition, an OECD report emphasized that in financial systems employing artificial intelligence and machine learning models, common issues include weak model governance, limited interpretability, and a high risk of strategy drift [13]. The findings of this study are highly consistent with the core logic of the existing literature, namely that quantitative trading systems are influenced not only by market volatility but also, to a significant extent, by methodological risks embedded in trading models.

Despite this overall consistency, the present study introduces several points of innovation or adjustment relative to prior research. Existing studies tend to focus more heavily on technical risks or system coupling issues, whereas this study finds that the combined weight of external environment risk and method risk is higher, and that changes in regulatory policy exert a more direct and pronounced impact on system risk than purely technical factors. Moreover, many international studies remain at the level of case analysis or theoretical frameworks. By contrast, this study employs the Analytic Hierarchy Process (AHP) to derive a ranked weighting of risk factors, thereby providing quantitative evidence from a practical perspective regarding which risks should be prioritized for management.

4.2. Risk prevention and response measures

In light of the above findings, this study proposes the following risk prevention and response strategies:

(1) A stress-testing and emergency response mechanism based on multi-scenario simulations should be established, encompassing macroeconomic conditions, regulatory policies, and extreme market events. Methods such as dynamic Value at Risk (VaR), historical scenario backtesting, and Monte Carlo simulation can be employed to assess system stability and capital resilience under different market conditions. At the same time, market monitoring indicators—such as volatility indices, cross-market correlations, and risk spillover measures—should be updated regularly, enabling timely adjustments to positions and strategy parameters in advance of market anomalies.

(2) During the model development and validation stages, cross-validation, rolling-window backtesting, and robustness testing mechanisms should be introduced to prevent model overfitting and strategy failure. A model lifecycle management framework should be established to ensure full-process traceability of model versions, parameter adjustments, and backtesting records.

Independent audits of strategy input data and trade execution logic should also be conducted to ensure consistency between live trading performance and design expectations.

(3) Close attention should be paid to changes in regulatory policies, trading rules, and taxation systems through the establishment of a "compliance update notification mechanism." Automated compliance modules can be embedded within quantitative trading systems so that alerts or forced suspensions are triggered when policy changes or abnormal trading behaviors are detected, thereby reducing the risk of regulatory violations.

(4) The separation of duties and dual-review mechanisms within teams should be strengthened to ensure checks and balances among trading, research and development, and operations. A comprehensive risk culture training program, together with incentive and accountability mechanisms, should be implemented to encourage technical staff, traders, and compliance teams to conduct independent risk assessments prior to strategy deployment, thus mitigating system risks arising from operational negligence or information asymmetry.

Through the implementation of these measures, a closed-loop risk management framework encompassing "identification–assessment–early warning–response" can be established, enhancing the robustness and adaptability of quantitative trading systems and providing solid assurance for their long-term operation in complex financial environments.

5. Conclusion

By integrating the 4M1E framework with the Analytic Hierarchy Process, this study achieves structured risk identification and quantitative prioritization for quantitative trading systems. On this basis, it proposes a priority-based management approach and corresponding response strategies tailored to production-level quantitative systems. The findings not only provide quantitative trading institutions with valuable references for scientific decision-making in risk identification, resource allocation, and system design, but also lay a theoretical foundation for the future development of more refined and dynamic risk monitoring models. Future research may incorporate multi-source information—such as news sentiment and macroeconomic indicators—to conduct integrated assessments of market and strategy risks, thereby further enhancing system adaptability and predictive capability in complex environments.

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