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Artificial Intelligence in Quantitative Global Macro Investing: Implementation Scenarios, Practical Challenges, and Future Trends

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Abstract: *Against the backdrop of continuous innovation in financial markets, quantitative trading strategies, characterized by data-driven decision-making, model-based analysis, automated execution, and controllable risk, have exerted a profound impact on insurance investment and risk management. In this context, the application path, technical mechanism and risk governance framework of artificial intelligence in global macro-quantitative investment are systematically discussed, focusing on the structured processing of multi-source heterogeneous data, non-linear factor mining, the role of deep learning and reinforcement learning in strategy generation, and the promotion effect of generative AI on factor construction and strategy iteration. The article further examines the robustness and adaptability of AI models in extreme market conditions, and proposes optimization strategies that take into account theory and practice for key links such as high-end interdisciplinary team construction, systematic research platform, intelligent data processing architecture, and risk management closed loop, and provides a systematic reference for realizing the intelligence, dynamics, and risk control of quantitative global macro investment.*

Keywords: *Artificial Intelligence; Financial Markets; Macro Quantitative Investment*

1. Introduction

The field of artificial intelligence (AI) in quantitative investment has seen significant advancements, yet it lacks a standardized benchmark aligned with industry practices[1]. The lack of standardized benchmarks makes the models proposed by different researchers or institutions lack unified measurement standards in key aspects such as data preprocessing, signal extraction, return evaluation price, and risk measurement, thus hindering the reproducibility and horizontal comparison of results. The lack of a standard system has also exacerbated the industry's uncertainty in AI model risk control, compliance assessment, and life cycle management, because the lack of reference specifications makes it difficult for the regulatory framework and internal control to form a stable closed loop. This is particularly prominent in the field of global macro quantitative investment and research. The macro signal itself has the characteristics of high-dimensional heterogeneity, time-varying unsteadiness, and low signal-to-noise ratio. If there is no common benchmark framework, it can easily lead to misjudgment in terms of model generalization ability, stress testing, and extreme state assessment, thereby amplifying the risk of strategy implementation. Based on this, building an AI quantitative evaluation system that is both in line with academic rigor and closely in line with practical needs is not only a necessary condition to promote AI-driven quantitative innovation towards industrialization, but also an important prerequisite for achieving cross-institutional collaborative progress and improving the overall efficiency of the market.

2. Overview of Quantitative Investment

Quantitative investment (abbreviated as “quant” in this paper) is an important part of the wealth management industry, which is one of the largest sectors of the world’s economy[2]. Modern quant applies rigorous mathematical and statistical modeling techniques, machine/deep learning techniques, and algorithmic trading techniques to discover asset pricing abnormalities in financial markets and profit from the following arbitrage or investment opportunities[3].At the theoretical level, quantitative investment is based on modern asset pricing and investment portfolio theory, covering the risk premium structure revealed by the capital asset pricing model (CAPM), arbitrage pricing theory (APT), and Fama-French and other multi-factor frameworks. Statistical methods are used to analyze the risk and return relationship of asset returns, so as to construct a systematic judgment mechanism for market prices deviating from the inherent value. Specific strategies are often verified through back testing of historical data, and the effectiveness of the strategy is evaluated through risk-adjusted performance indicators such as Sharp ratio, Jensen alpha, and value at risk (VaR), and the combination of risk budget and constraints optimizes the performance of the technology to stabilize the combination.

Quantitative investment is not only related to the accuracy of the model, but also emphasizes the synergy between the model and risk control. For example, when using machine learning models to predict future returns in a big data environment, it is also necessary to combine rigorous data preprocessing, robustness testing, and the automated execution mechanism of the real-time trading system to ensure the stability and maintainability of the strategy in the actual market[4].This interdisciplinary integration includes not only the processing of high-dimensional and heterogeneous data, but also a deep understanding of the economic logic and market microstructure behind asset prices, making quantitative investment both a theoretical system and an operational investment project.

3. The Key Role of Artificial Intelligence in Quantitative Global Macro Investment

3.1 Data Collection, Cleaning and Accuracy Assurance

In the global macro-quantitative investment system, macro indicators, interest rate and exchange rate sequences, high-frequency data in the trading market, commodity prices, and even news texts and social media signals constitute an extremely complex multi-source heterogeneous data ecosystem[5]. These data are difficult to directly use for model training and strategy construction due to missing values, inconsistent formats, and noise interference. In actual data science practice, the workload of data collection and cleaning in the entire data analysis life cycle is often extremely uneven-according to the industry questionnaire 1, when data scientists do not have advanced automation tools, up to 60%-80% of their time is spent on data cleaning and preprocessing, including Cleaning and organizing data accounted for about 60%, while collecting data accounted for about 19%.This proportion not only reflects the universality of data quality problems, but also shows that high-quality data is the decisive prerequisite for the effective learning and generalization of AI-driven models. Based on this, AI technology is introduced in the macro-quantitative investment scenario, and machine learning and natural language processing are used to automatically identify and structure raw heterogeneous data, which can significantly reduce data cleaning time, improve the accuracy of missing value filling and noise filtering capabilities, so as to transform the pre-stage that originally consumed most of the resources into a controllable and measurable input matrix optimization process. This not only provides a high-quality, semantically consistent data foundation for deep learning models and reinforcement learning strategies, but also makes the next modeling activities such as factor mining and emotional index quantification have a solid data base and statistical reliability (see table 1).

Table 1 Typical time distribution of data cleaning and preparation links

Data processing stage	Typical time ratio
Data cleaning and pretreatment	60%
Data collection and integration	19%
Pattern mining and analysis	9%
Model training and parameter adjustment	3%
algorithm refinement, etc.	4%

3.2 Data Security and Compliance Management

With the deep penetration of AI technology into the global macro-quantitative investment field, data security and compliance issues have gradually become the core challenges of institutional and technological resonance[6]. When quantitative investment institutions build and train AI models, they must process sensitive information including transaction instructions, investor behavior logs, and market transaction flows. Once this information is leaked, it may cause market manipulation risks or regulatory penalties. Therefore, artificial intelligence systems must be embedded with sound data governance and security policies. For example, the FEAT principles issued by the Monetary Authority of Singapore (MAS) emphasize that AI systems should ensure fairness, accountability and transparency, and provide specific guidance on data source selection, data quality evaluation, and privacy protection to prevent unauthorized use of data and the spread of risk of model output. This means that in the quantitative model training process, not only the original data must be encrypted, stored and access rights verified, but also the review and recording system of AI-generated content must be established to meet the requirements of multinational supervision for AI interpretability and traceability. In particular, the automated decision-making process of large-scale language models requires transparent strategies, including model input audit, feature source labeling, inference path recording, and abnormal behavior logs. These are all pre-measures to avoid compliance risks caused by “black box” decision-making.

3.3 Model Design, Training, and Adaptability

In quantifying global macro-investment, the model design and training process reflect the close intertwining between AI technology and financial theory. Traditional quantitative strategies rely on statistical regression and linear factor models to capture historical laws. Such methods have advantages in model interpretability and economic theory support, but they are powerless in the face of high-dimensional nonlinear relationships and heterogeneous information. Modern AI models, especially deep neural networks, sequence prediction models, and large-scale language models (LLMs), can mine complex structural signals from high-dimensional nonlinear data, while combining graph neural networks and reinforcement learning methods to deal with sequence dependence and dynamic interaction. For example, the large-scale language model introduced in quantitative research can automatically identify the potential logical relationship between news, policy texts and market data, so that unstructured characteristics such as emotional factors and policy expectations can be quantified and incorporated into model training. A further multi-agent collaboration framework can modularize tasks such as market data conversion, feature construction, and model verification, and collaborate with different agents to optimize investment strategies. This not only improves the efficiency of model training, but also enhances the diversity and robustness of the strategy portfolio. In addition, the adaptive learning mechanism allows the model to continuously update parameters in the real-time data stream, effectively responding to market structure changes and model drift, so that the strategy has the ability to dynamically adjust, thereby improving the generalization performance and real-market performance of the model in the real market environment.

3.4 Coping with Market Fluctuations and Extreme Events

The volatility and extreme event characteristics of the global macro-investment system, such as financial crises, sudden policy changes, or geopolitical shocks, often cause traditional models that fit historical samples to fail outside the sample. To this end, the AI method constructs a high-dimensional situational space and a complex market behavior simulation framework to make the strategy more robust and adaptable in the face of these extreme states. Specifically, AI can integrate heterogeneous data (including market prices, macro indicators, and real-time news events, etc.) and generate probabilistic assessments of future fluctuations, enabling investment portfolios to adjust positions before systemic risks arise. In addition, the researchers have also developed a risk prediction model based on deep learning, which combines time series analysis and sentiment signal extraction to capture market fluctuations and tail risks. The performance is higher than that of traditional econometric models. Some innovative frameworks also use multi-modal fusion technology to integrate information from different data sources into risk assessment models, so as to more fully reflect potential risk factors in an extremely volatile environment. Through continuous online learning and model fine-tuning mechanisms, this kind of AI prediction model can adapt to changes in market structure, maintain a low level of error, provide real-time risk prediction and risk mitigation capabilities for global macro investment strategies, and significantly improve the robustness of strategies under extreme conditions.

4. Evolution of Artificial Intelligence in Quantitative Macro Investment Strategy

4.1 Traditional Quantification Phase

In the initial stage of global macro-quantitative investment, the strategy is mainly based on the framework of mathematical statistics and econometrics, and the relationship between market microstructure and macro variables is characterized through traditional factor analysis, linear regression and optimization models[7].The core of this stage is to construct a regression factor system with strong interpretability and limited parameters, such as the capital asset pricing model (CAPM), Fama French three-factor model, etc., by fitting historical samples to discover the average effect of asset pricing; the strategy realization process often relies on human experts to manually screen factors, manually set parameters, and perform regression assessments based on a single data source. Although this method has a clear theoretical basis and strong interpretability, it faces problems such as weakening linear assumptions, model mismatches caused by variable heterogeneity and non-stability in actual market operation, making it difficult to effectively capture complex market interactions and dynamic changes.

4.2 Machine Learning and Deep Learning Phase

After entering the machine learning and deep learning stages, the quantitative strategy has evolved from a traditional linear framework to a powerful nonlinear model, thereby overcoming the limitations of traditional methods in processing high-dimensional complex relationships and heterogeneous data. Machine learning algorithms (including support vector machines, random forests, gradient lifting trees, etc.) and deep neural networks (such as multi-layer perceptions, recurrent neural networks, and convolutional neural networks) have been introduced into data mining and pattern recognition, enabling strategies not only to automatically extract deeper signals from traditional price and factor sequences, but also to absorb a large amount of alternative data, such as news emotions, satellite images, etc., to achieve joint modeling of multi-modal inputs.

4.3 Generative AI and Intelligent Decision-Making Phase

Under the framework of global macro—quantitative investment, the maturity of generative artificial intelligence and large—scale language models marks the transition of the strategy system from “prediction-driven” to an integrated intelligent decision-making paradigm of “cognition-generation-execution”[8]. Its core is not simply to improve the prediction accuracy, but to reconstruct the Alpha production function through semantic modeling and strategy generation capabilities. The large model represented by GPT-4 based on the Transformer architecture can embed high—dimensional semantics of central bank policy statements, financial reports, management interviews, and cross—language news texts, mapping policy tendencies, emotional offsets, and institutional constraints that were originally difficult to quantify into a continuous vector space, and cross—modal integration with structured macro variables; on this basis, a multi-agent collaborative mechanism and an enhanced learning framework (Figure 1) are introduced to enable the model to realize adaptive iteration of strategies in the closed loop of factor generation, screening, weight distribution, and risk feedback. Empirical research shows (Table 2) that in a mixed model that contains textual emotion factors and traditional macro factors, the information ratio is about 15%-30% higher than the benchmark model that uses only structured variables. At the same time, the factor coverage and candidate index generation efficiency are significantly improved, reflecting the marginal contribution of generative AI in Alpha search space expansion and dynamic weight optimization.

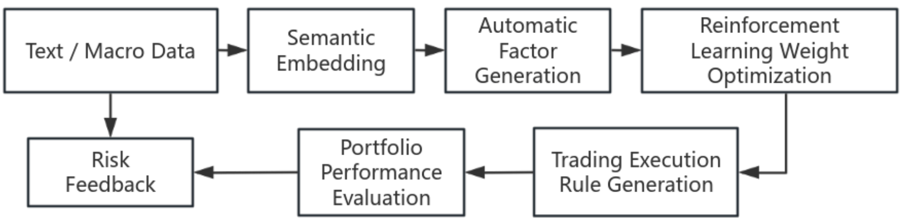

Figure 1 Schematic diagram of the closed-loop structure of intelligent decision-making

Table 2 Comparison of strategy performance before and after the introduction of generative AI

indicator	Traditional macro factor model	Fusion generative AI model
Annualized rate of return	12.4%	15.8%
Information ratio (IR)	0.78	1.02
Maximum drawdown	−14.6%	−11.2%
Factor generation efficiency (candidate/month)	25	140

Description: The example is based on a multi-asset macro back testing framework, and the sample interval is assumed to be a 10-year rolling window; the “fusion generative AI model” introduces text embedding factors and enhanced learning dynamic weight distribution mechanism.

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5. Challenges of Artificial Intelligence in Quantitative Global Macro Investment

5.1 Shortage of High-end Talents and Interdisciplinary Teams

In the construction of a macro-quantitative investment system driven by artificial intelligence, talent shortcomings have become the core bottleneck restricting innovation and real market landing. Unlike the relatively single economic and statistical background in traditional financial research, AI quantitative research requires the integration of multi-disciplinary knowledge such as investment theory, statistical learning, natural language processing, high-performance computing architecture, and financial engineering within the same framework. This not only involves the understanding of model algorithms, but also requires deep insight into market structural risks, the hidden mechanism of extreme events, and the dynamic formation mechanism of asset prices. However, in the actual industry, composite talents who can combine deep quantitative theoretical understanding and actual AI engineering realization capabilities are extremely scarce, and it is often difficult to establish effective collaboration mechanisms between existing financial practitioners and AI developers due to professional barriers. Although universities and research institutions have gradually launched related courses, there is still a significant lag from the design of the curriculum system to the effectiveness of talent training, which leads to the actual team often relying on narrow technical experts or researchers in a single field when building the AI quantitative framework, unable to form a truly interdisciplinary synergy, which in turn affects the robustness and interpretability of AI models in complex market environments.

5.2 Insufficient Systematic Research and Decision Support

At present, most financial institutions' AI quantitative research is still stuck in the technical pilot at the level of strategic components, and they lack a truly systematic research framework and a cross-departmental collaborative decision-making support system. On the one hand, quantitative research teams often form an "island-style" working model between model design, experimental verification, and real-world strategy deployment, and lack a unified model life cycle management, version control, risk index system, and performance attribution analysis methods, which directly leads to the difficulty of strategy promotion to form a repeatable and verifiable industry standard. On the other hand, the traditional investment decision-making chain has not yet fully adapted to the non-linear, dynamic interactive signal generation and portfolio optimization needs driven by AI. When faced with model complexity, insufficient transparency, and explanatory issues of AI output, many investment committees still have difficulty giving scientific risk budget and strategy selection opinions, making the output of AI models often decoupled from the final investment decision, weakening its decision-making contribution in macro judgment and asset allocation.

5.3 Insufficient Large-scale Data Processing and Intelligent Framework

The data ecology of global macro-quantitative investment is essentially a high-dimensional, heterogeneous, real-time continuous flow data system, including multi-modal information such as macroeconomic indicators, cross-market prices, derivative data, unstructured texts, and public opinion. This puts forward extremely high requirements for the scale, structural consistency, low-latency processing power, and interpretability of data pipelines. At present, the data infrastructure of most institutions is still limited to traditional data warehouses and offline processing architectures, making it difficult to efficiently cope with the needs of real-time streaming data integration, feature engineering automation, cross-asset class data linkage and model input integration. In contrast, the sensitivity of AI models to large-scale data-such as deep learning, reinforcement learning, and large-scale language models-is extremely dependent on data quality and quantity during training. At the same time, the real-time reasoning stage also requires low-latency and high-availability computing environment support. In industrial practice, many financial institutions have tried to introduce cloud computing, distributed data frameworks, feature storage, and automated MLOps, but there are still significant shortcomings in data security isolation, elastic scheduling of computing power, and real-time monitoring. This not only affects the efficiency of model training, but also weakens the adaptive ability of the model under market mutations.

5.4 Incomplete Risk Management and Strategy Optimization System

In global macro-quantitative investment, risk management is by no means a simple after-the-fact

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control mechanism, but should be deeply integrated into the whole process of strategy generation, position decision-making, execution and dynamic adjustment. Traditional risk management frameworks usually rely on preset statistical indicators (such as VaR, CVaR, etc.) or linear risk factors, which are often powerless for the high-dimensional nonlinear risk characteristics mined by AI, making strategies lack effective early warning mechanisms when they are exposed to systemic risks in extreme market conditions. The optimization of AI quantitative strategies must not only focus on absolute returns, but also adjust risk tolerance and trading strategy parameters in real time in the dynamic market volatility structure. At this stage, the industry still lacks an intelligent risk measurement system that can operate in concert with AI predictive models. For example, deep learning-driven tail risk prediction and multi-modal signal fusion integrated risk assessment framework have not yet formed an industry standard. Further, risk management should achieve a closed loop of strategy optimization through adaptive threshold mechanisms, intelligent position adjustment algorithms, and real-time monitoring systems, but in practice these mechanisms often exist independently of predictive models and are difficult to directly couple with the internal logic of AI models. If an intelligent optimization system that can simultaneously adjust the strategy and risk tolerance is not established, the AI-generated strategy will face significant risk exposure and retracement risks in large-scale capital operations and actual market execution, making it difficult to guarantee long-term stable performance.

6. Application Path of Artificial Intelligence in Quantitative Global Macro Investment

6.1 Building a High-end Talent and Interdisciplinary Investment Team

When building a quantitative global macro-investment system with artificial intelligence as the core driving force, talent and team structure are basic strategic resources, which determine the cognitive boundaries, innovation capabilities, and comprehensive control of markets, technologies, and risks of the entire AI quantitative system[9]. Traditional financial institutions focus on financial analysts, macroeconomic researchers, and traders. In the process of AI quantitative transformation, the talent structure and collaboration model must be reshaped to incorporate computer science, statistics, machine learning engineering, natural language processing, big data architecture, and investment strategy research and other interdisciplinary capabilities into the same team to achieve the integration of knowledge boundaries through cross-disciplinary collaboration. On the one hand, institutions need to recruit data scientists and AI engineers with practical experience. They not only understand the principles and constraints of machine learning algorithms, but also perform feature engineering and model tuning verification in actual market data. On the other hand, macro researchers and financial engineering experts undertake the review of the economic meaning of the input and output of the AI model, explanatory analysis, and risk control of the core logic of the strategy to ensure that the model output is not only statistically significant, but also economically significant. Such interdisciplinary teams usually need to establish clear communication and collaboration standards, such as the establishment of AI strategy development cycle management, model inspection process, abnormal output review system, back testing and real-world deployment bridging mechanism, etc. This mechanism not only improves R&D efficiency, but also can gradually form a knowledge accumulation and strategy library within the team.

In terms of talent training, institutions also need to establish continuous learning and internal training systems, such as by organizing joint seminars on AI algorithms and financial quantitative analysis, case reflection sessions, and cooperation projects with universities/laboratories to absorb the latest research results and internalize them in time into practical strategies. The selection of talents should have both theoretical skills and real-world experience: not only must they have a solid foundation in statistical learning and model interpretability research, but they must also have a deep understanding of engineering issues such as real-world trading, order execution, and computing power resource scheduling. In addition, the design of cross-team incentive mechanisms is also essential. The success of AI quantitative teams depends not only on individual contributions, but also on the overall performance of the system of module collaboration. Therefore, the organizational structure should avoid the “silo effect” and establish a stable and effective ecology through cross-departmental transparent collaboration, technology and investment sharing measurement system, and return-linked performance appraisal mechanism, so as to form a replicable organizational ability in the process of global macro-quantitative investment landing, rather than relying solely on an algorithm or the isolated ability of a few experts.

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6.2 Improving the Systematic Research and Decision Support Platform

Establishing a systematic research and decision-making support platform that can support artificial intelligence-driven quantitative global macro-investment is a key engineering task to promote the implementation of theory and practice. This platform essentially needs to build a closed-loop ecosystem with data as the core, model as the driver, and strategy as the goal, so that every step from data collection, feature construction, model training, strategy testing to real-world execution can operate smoothly under a unified architecture, and has strict controllability and auditability.

At the data level, the platform should be able to support multi-source data access from global macro indicators, market conditions, derivative prices, news texts, policy announcements and even alternative data (such as satellite images, traffic flows, etc.), and have a unified data governance mechanism to ensure data format consistency, time synchronization and quality controllability. On this basis, through an efficient data lake and data warehouse system, as well as a distributed computing framework (such as Spark or a distributed database), it is possible to clean, aggregate, index, and update large-scale data in real time, which has laid a solid foundation for subsequent AI model training and real-time strategy adjustment.

At the model development level, the platform needs to integrate mainstream machine learning, deep learning, and natural language processing tools to enable quantitative researchers to flexibly call algorithm resources, while ensuring that all model training processes have traceable version control and metadata management. The platform should provide standardized model training process templates and automated evaluation tools, including modules such as cross-verification, hyperparameter search, overfitting detection, and model explanatory analysis, and be equipped with visualization tools to help researchers understand the economic logic and potential risks of model output. In addition, in order to improve the efficiency of strategy development, the platform should support a strategy back testing engine, seamlessly integrate with historical data, and allow researchers to conduct rigorous benefit and risk testing of strategies under consistent conditions, and iterate and optimize strategies based on the back testing results. A further advanced platform will adopt an A/B testing mechanism to conduct controlled trials of strategies in simulated real markets and small-capital real markets to shorten the time window from strategy development to actual deployment.

At the decision support level, the platform needs to build a unified strategy performance analysis module to enable the research, risk and trading teams to understand the benefits, risk exposure, transaction costs and execution effects of the strategy in real time, while providing early warning signals in combination with real-time market conditions. In addition, it can also be combined with adaptive AI algorithms to provide intelligent adjustment suggestions for investment strategies. For example, when the market volatility exceeds the historical normal range, the platform automatically calculates adjustment recommendations and supplements them with risk assessment reports for the reference of the investment decision-making committee. In the end, such a research and decision support platform is not only a technical tool, but also a core center to improve the productivity of quantitative research, risk control capabilities, and strategy execution efficiency of institutions, helping to form an operational, replicable, and scalable intelligent investment system.

6.3 Building a Large-Scale Data Processing and Intelligent Framework

The construction of large-scale data processing and intelligent framework is the underlying engine for the transformation of AI-driven quantitative global macro investment from theory to reality[10].Since macro market signals usually come from multi-level, heterogeneous data sources, including high-frequency price data, structured economic indicators, policy texts, news and public opinion, and industry alternative data, an intelligent data processing framework that can support high throughput, low latency, and high extensibility is needed. At the practical level, this requires the adoption of distributed storage and computing systems, such as the use of distributed file systems and distributed computing frameworks (such as Hadoop, Spark, and modern cloud-native architectures) to handle data fusion, cleaning, indexing, and feature engineering. In addition, the framework should also support real-time streaming processing, so that market data, real-time news, and social media signals from exchanges can be captured, analyzed, and incorporated into AI training and strategy judgment within a very short delay, which is particularly important for real-time risk control and strategy execution efficiency.

The first step in building a large-scale data processing and intelligence framework is to formulate data standardization specifications, including time synchronization, Gregorian calendar and market

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transaction time zone conversion, data deletion processing rules, noise rejection standards, etc., so that cross-market and cross-asset data has unified processing standards at the beginning of entering the system, and then the data is pushed to different computing nodes through intelligent pipeline tools. On this basis, the Feature Store is used to manage the cleaned and preprocessed feature data, so that the features can be shared between model training and real-time reasoning, and it has version control and online monitoring capabilities. Such a design not only improves the efficiency of data reuse, but also provides the basis for the interpretability and traceability of the model. Secondly, in order to improve the extensibility of the intelligent framework and the efficiency of algorithm scheduling, containerization and microservice architectures should be introduced to enable model training, assistant adjustment, strategy simulation, and deployment modules to be independently upgraded and dynamically expanded, and through a unified scheduling system (such as Kubernetes) to achieve flexible resource allocation.

At the level of intelligent reasoning, the design model reasoning service can execute AI predictions in a low-latency manner in the real-time market data stream, and generate specific buying and selling signals in combination with strategic logic. This service is usually driven by a high-performance inference engine and equipped with a real-time monitoring mechanism for detecting model failures, data drift, and abnormal output. At the same time, online A/B comparative testing of the model should be implemented to facilitate timely downgrading or replacement when performance degradation is found. In terms of model iteration, the intelligent framework should support automated ML Ops processes, including model version management, continuous verification, automatic rollback and other mechanisms, so as to build an AI quantitative system that can continue to evolve in market changes.

6.4 Risk Management and Intelligent Strategy Optimization

In the quantitative global macro-investment system, risk management is not a simple after-the-fact control mechanism, but a systematic function deeply coupled with strategy generation, execution and dynamic adjustment. The purpose of the introduction of artificial intelligence technology into risk management is not only to improve the accuracy of traditional risk measurement, but also to embed risk management into the entire strategy life cycle, so that it has intelligent risk screening and adaptive adjustment capabilities in signal generation, position decision-making, order execution and even portfolio rebalancing. In practice, this system needs to cover both static and dynamic risks: static risk involves the evaluation of indicators such as historical volatility, risk exposure, credit risk, and the possibility of extreme losses; dynamic risk involves risk-weighted adjustments based on real-time market conditions, such as real-time volatility prediction and tail risk prediction[11].

First of all, a comprehensive risk index system should be constructed, including traditional VaR, CVaR, volatility prediction, defensive risk indicators, etc., while combining AI methods for more complex nonlinear risk prediction .For example, the simulation of extreme events in market history through deep learning models enables the system to identify potential systemic risks in advance when the market volatility structure changes, and trigger strategy-level risk intervention. This AI-enhanced risk model can be combined with real-time data streams to conduct secondary screening of each transaction recommendation through a real-time risk scoring mechanism, so as to avoid the amplification of losses caused by blind execution of signals in structural fluctuations. In addition, through the adaptive threshold and risk budget mechanism, the system can automatically adjust the risk tolerance at different market stages, and optimize the portfolio weight and risk distribution through intelligent optimization algorithms, so that the overall portfolio maintains a more stable performance when it is exposed to systemic risks [12][13].

At the level of strategy optimization, risk adjustment should be incorporated into the objective function. By introducing a benefit optimization model with risk penalties, the strategies generated by AI should not only pursue absolute benefits, but also pay more attention to the dynamic balance between risk and benefit. Specifically, the net worth drawdown constraints, maximum drawdown restrictions, and asymmetric risk appetite adjustments can be adjusted simultaneously during the strategy back testing and real-market deployment process, so that the strategy has a higher survivability while pursuing Alpha. Through an embedded risk assessment system, an intelligent position adjustment mechanism, and a real-time monitoring and early warning system, institutions can adjust their risk exposure in a timely manner in the face of market fluctuations that deviate from the historical norm, and improve strategic robustness through continuous learning and optimization mechanisms. Such an intelligent risk management system is not only a technological upgrade of traditional quantitative risk control, but also a necessary condition for the sustainable development of quantitative global macro investment in a complex market environment[14][15].

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7. Conclusion

With the improvement and maturity of China's capital markets, data-driven quantitative trading, known for its objectivity, high frequency, and automation, has gradually developed into an important trading method in the financial market. The application of AI in global macro-quantitative investment has enabled the strategy to evolve from static prediction to dynamic adaptation, from single-factor decision-making to multi-modal intelligent portfolio, and at the same time closely coupled with the closed loop of risk management, improving the robustness of the investment portfolio under extreme events and market fluctuations. In the future, the collaboration of interdisciplinary talents, the improvement of intelligent research platforms, and the construction of large-scale data processing and adaptive strategy optimization systems will become the core driving force to support the continuous innovation and steady development of quantitative global macro investment, and provide a solid theoretical and practical foundation for efficient resource allocation and risk control in the capital market.

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