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Empirical Analysis of Short-Term Volatility Prediction and Robustness of the Shanghai Composite Index by Integrating Technical Indicators and LSTM Model

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Abstract: The Shanghai Composite Index (SSE) is heavily influenced by policy, has a complex capital structure, and is amplified by market sentiment, making it valuable for short-term volatility prediction. Addressing the challenge that traditional linear models struggle to simultaneously characterize the nonlinearity, non-stationarity, and long-short dependence of financial time series, this paper, based on a review of English-language research over the past three years and combined with publicly available monthly statistics from the Shanghai Stock Exchange, conducts a descriptive empirical analysis of the SSE's closing price and monthly changes from January 2025 to February 2026. A short-term prediction framework using returns, normalization, LSTM state updates, and mean squared error loss is proposed. The SSE exhibits a phased pattern of low-level recovery, mid-term oscillation, and subsequent rise during the sample period. Monthly volatility increases significantly under policy and liquidity shocks. LSTM demonstrates better adaptability than traditional models in terms of continuous dependence, trend reversals, and indicator absorption. Based on this, improvements to the short-term prediction system are proposed, including feature engineering, model structure, rolling training, risk constraints, and interpretation mechanisms, providing insights for index prediction research and quantitative investment decision-making.

1 Introduction

Financial market forecasting has always been a topic of interdisciplinary research in quantitative finance and artificial intelligence. Compared with individual stock prices, index sequences are better able to reflect changes in the overall market risk appetite and macroeconomic expectations. Therefore, the identification of short-term fluctuations in the Shanghai Composite Index involves not only issues of trading timing and asset allocation efficiency, but also market risk monitoring, policy judgment, and investor behavior research. In recent years, due to the rapid expansion of deep learning technology in sequence modeling, Long Short-Term Memory Networks have been widely used in many problems such as stock returns, index prices, directional classification, and sentiment-driven predictions due to their ability to preserve long-term dependencies [1-4].

In China's capital market, the Shanghai Composite Index is influenced by numerous factors, including liquidity conditions, policy windows, industry rotation, northbound capital flows, and market sentiment fluctuations. These factors largely contribute to the Shanghai Composite Index's pronounced nonlinearity and structural abrupt changes. Traditional models such as ARIMA and GARCH can effectively characterize local linearity and volatility clustering, but their adaptability to environments with high noise, high uncertainty, and heterogeneous information is relatively low, particularly regarding trend abrupt changes and complex interactions. Therefore, linking technical indicators with the LSTM architecture to create a short-term forecasting model that better reflects actual market conditions has significant theoretical implications and practical urgency.

Therefore, this paper specifies the title as "Short-Term Volatility Prediction of the Shanghai Composite Index and Empirical Analysis of Robustness Based on the Integration of Technical Indicators and LSTM Models." The paper first summarizes the latest applications of LSTM and its variants in securities forecasting. Then, based on monthly statistics published by the Shanghai Stock Exchange, it conducts descriptive statistics on the performance, volatility, and returns of the Shanghai Composite Index during the sample period. Next, it discusses the shortcomings of existing research in areas such as data granularity, feature fusion, model interpretation, and risk control, and proposes improvement ideas for short-term forecasting. The entire paper unfolds in the logical order of introduction, current situation analysis, problem statement, problem-solving or strategy, and conclusion.

2. Current Status Analysis of Short-Term Forecasting Research on the Shanghai Composite Index

The English literature of the past three years shows that the main focus of research on stock and index prediction has gradually shifted from fitting a single price series to multi-source data fusion and deepening the hierarchical structure improvement. Si et al. used the opening price difference of the Shanghai Composite Index from 1990 to the present as a sample to compare ARIMA, LSTM, GRU and hybrid models. They found that ARIMA-LSTM and ARIMA-GRU had better error indices than single models, indicating that there are obvious advantages to combining statistical models and deep models [1]. Sang and Li improved the gating structure and added an attention mechanism to improve the model's adaptability to sudden fluctuations and abnormal noise, and made LSTM more robust in price prediction [2].

Kalra et al. proposed a hybrid bidirectional LSTM model, combining incremental learning mechanisms and technical indicator inputs, which can make real-time predictions for various stock indices. Its mean absolute percentage error is significantly reduced, indicating that deep models have good application prospects in high-frequency update scenarios. Papageorgiou et al. combined reinforcement learning with data beyond price series, analyzing it in a volatile environment, and found that sentiment information can also be incorporated into the system to improve the quality of short-term trading decisions. This shows that modern financial forecasting no longer focuses solely on a single sequence; it emphasizes multiple factors of information and the speed of updates, while also considering the reproducibility of the model.

Compared with foreign multi-market research, research on China's A-shares, especially the Shanghai Composite Index, has been increasing in recent years. Gao used daily data of the Shanghai Composite Index in 2020, 2021, 2022 and 2023 as a basis to establish a trend prediction model using the LSTM model. He used the Monte Carlo method to test the Q4 trend and found that the LSTM is feasible for trend identification in the Chinese market [5]. Dong and Liang combined CNN, LSTM and graph neural network to predict A-share stocks and proved that joint modeling of technical indicators and structural relationship information can significantly improve the ability to judge returns and trends [7]. At the same time, Liu, Rajpal and others have shown that the competition of short-term prediction models in the future will focus more on the quality of feature performance, whether the direction is correct, and the ability to limit asymmetric risks [6][8].

In addition, sentiment text and multimodal information are gradually being regarded as important variables for improving short-term prediction. Chuang et al. took Chinese financial news as the basis and compared the situation of many word embeddings, deep models and large language models in terms of sentiment classification and short-term stock price regression. They concluded that LSTMs have a relatively stable prediction level in different volatility groups. Wang et al. used news sentiment features, transaction-related indicators and blockchain credibility mechanism to propose a safer and more reliable prediction model for LSTM[9]. In summary, there has been great progress in model structure and information fusion, but there are still areas for improvement in interpretable modeling, rolling robustness testing and risk constraint design for the Chinese index market.

When modeling short-term volatility, the price series must first be transformed into a return series to reduce scaling differences and improve stationarity. The monthly return defined in this paper is as follows:

$$\mathrm{rt} = (\mathrm{Pt} - \mathrm{Pt} - 1) / \mathrm{Pt} - 1 \tag{1}$$

In equation (1), P_t is the closing price in period t, and r_t is the corresponding rate of return. Using the rate of return instead of the original price to build the model better reflects the strength of short-term market fluctuations.

To avoid model training distortion caused by different feature dimensions, the input variables must be normalized. The following two methods are commonly used.

$$\mathrm{xt}' = (\mathrm{xt} - \mathrm{xmin}) / (\mathrm{xmax} - \mathrm{xmin}) \tag{2}$$

Equation (2) unifies price, trading volume, and technical indicators onto the same dimension, which makes gradient updates more stable and less susceptible to local extrema.

3. Major problems in predicting short-term fluctuations of the Shanghai Composite Index

While LSTM and its extended models demonstrate excellent sequence learning capabilities for short-term security forecasting, current research suffers from several common shortcomings. Data granularity is often too fine and lacks completeness. Some studies use minute-by-minute or daily data, while others use coarser monthly or event-window data; the meanings and noise structures of these different frequencies vary. Without a unified mechanism for data cleaning, outlier handling, and time alignment, model training can treat market noise as valid signals, leading to unstable predictions.

Secondly, feature engineering still tends to prioritize price over mechanism. Many studies rely heavily on basic indicators such as opening price, closing price, highest price, lowest price, and trading volume. While these variables are crucial for technical analysis, neglecting external factors like changes in margin balances, market turnover rates, volatility accumulation, policy timing, northbound capital flows, and sentiment analysis makes it difficult for models to accurately reflect how policy shocks and capital behavior amplify multi-period fluctuations in the Chinese market. Furthermore, when indices rise or fall rapidly, relying solely on historical price information makes it difficult to promptly identify turning points.

Furthermore, poor interpretability of the model also renders LSTM predictions unusable. While deep learning models outperform traditional models in terms of error metrics, investors and researchers are more concerned with the reasons behind the model's predicted rises and which feature is most important in the current stage. If the output results cannot be explained using methods such as attention weights, feature contribution, and rolling sensitivity analysis, then even if the model is effective in backtesting, it is difficult to turn it into an actionable risk management tool. For composite indices like the Shanghai Composite Index, which are influenced by multiple factors, insufficient explanation significantly reduces the model's decision-making value.

Finally, many studies emphasize prediction accuracy but fail to consider the relationship between trading constraints and risk constraints. Short-term predictions are not tradable returns. If directional accuracy, drawdown control, signal stability, and turnover costs are not incorporated into the same evaluation system, the problem of "good in-sample fit but poor out-of-sample returns" will arise. Therefore, simultaneously considering error minimization, directional judgment, overfitting suppression, and risk budgeting in LSTM prediction models is a crucial issue that current research on short-term predictions of the Shanghai Composite Index must address.

4. Problem-solving approaches and strategies

This paper argues that the prediction of short-term fluctuations in the Shanghai Composite Index should be systematically improved from five aspects: data, features, models, validation, and risk control. Firstly, data processing should establish a multi-frequency data collaboration mechanism. High-frequency or higher-frequency samples can be aligned according to a unified trading calendar, and supervised learning samples can be constructed using a sliding window. Monthly publicly available statistical data can be used for phased trend identification and robustness verification. Layering data according to different frequencies can maintain the model's high sensitivity to high frequencies while ensuring high stability for low frequencies.

Secondly, in feature engineering, the single price series should be transformed into a mixture of multiple technical indicators. In addition to returns and trading volume, variables such as moving averages, relative strength index (RSI), Bollinger Band width, volatility proxy variables, turnover rate, turnover characteristics, and sentiment scores can be added. Correlation screening, principal component compression, or attention mechanisms can be used to allocate feature weights. This leverages the time-dependent learning characteristics of LSTM while improving the model's responsiveness to changes in market structure.

Third, in terms of model structure, a convolutional or attention-based front-end combined with an LSTM main body and a fully connected output layer can be used. The front-end convolutional layer extracts local fluctuation patterns, the attention mechanism identifies important time steps, and the LSTM maintains long-term connections. The final output depends on whether the research task is to predict or classify continuous values. For the short-term fluctuation scenario of the Shanghai Composite Index, if the goal is to provide trading signals, then direction classification and fluctuation range prediction are more practical than simple point fitting; if the goal is to study the phase changes of the market, then both continuous value and range results should be provided.

Fourthly, during validation, rolling training and rolling testing need to be carried out simultaneously. Traditional random partitioning can disrupt the temporal relationships of financial time series, leading to information leakage. A more reasonable approach is to use extended windows or sliding windows to train, validate, and test by moving the timeline forward. Furthermore, evaluation metrics should not only include mean squared error, but also mean absolute error, directional accuracy, hit rate, and threshold-based risk identification capabilities to jointly assess the model's suitability for market decision-making.

Fifth, in terms of risk management, the predictive model must be considered an integral part of the overall risk architecture. On the one hand, asymmetric loss functions can be used to improve the model's ability to identify downside risks, paying more attention to erroneous bullish behavior during periods of high volatility. On the other hand, attention heatmaps, feature ablation experiments, and phased error decomposition should be used to explain why the model performs differently in different market environments. Only when the prediction results are interpretable, verifiable, and binding will LSTM's prediction of short-term fluctuations in the Shanghai Composite Index have practical application value.

In terms of its internal mechanism, LSTM's adaptability to financial time series stems from its gated update memory units, which can retain useful historical information even in noisy market sequences. Its basic state update can be represented as:

$$\mathrm{Ct} = \mathrm{ft} * \mathrm{Ct} - 1 + \mathrm{it} * \mathrm{Cnew} \tag{3}$$

In equation (3), the memory state is represented by C_t, the forget gate by f_t, the input gate by i_t, and the candidate state by Cnew. It can simultaneously retain long-term trend information and selectively absorb new market shocks.

After updating the memory, the hidden state also needs to be output for later use. The expression for this can be written as follows:

$$\mathrm{ht} = \mathrm{ot} * \tanh(\mathrm{Ct}) \tag{4}$$

In equation (4), h_t is the hidden state and o_t is the output gate. The hidden state contains all the effective information from the past period and is a key element in making the fluctuation prediction result for the next period.

5. Descriptive Empirical Analysis

Based on publicly available monthly data from the Shanghai Stock Exchange from January 2025 to February 2026, this paper conducts a descriptive empirical study of the Shanghai Composite Index. The sample shows that after a brief correction at the beginning of 2025, the index began to recover, exhibiting a clear upward trend in August 2025. Although there were some fluctuations in November, the upward trend continued, and the index moved upward again at the beginning of 2026. The average closing point during the sample period was 3606.49 points, with a highest value of 4162.88 points and a lowest value of 3250.60 points. The average monthly change was 1.64%, with a standard deviation of 3.18%. The results indicate that short-term fluctuations in the Shanghai Composite Index are not simple random disturbances but exhibit distinct phased characteristics. This coexistence of trend continuation and local abrupt changes on LSTM can be described using a gated memory mechanism.

Table 1 shows the monthly closing prices and changes during the sample period of this study. The closing point rose from 3250.60 to 4162.88, but the rise was not unilateral; it was a gradual increase after several pullbacks. This table indicates that the Shanghai Composite Index exhibits both trends and volatility. During the sample period, models can be constructed using returns, price levels, and time sequences, but cannot be judged solely by static averages or changes in a single month.

Figure 1 shows the monthly closing price changes of the Shanghai Composite Index during the sample period. Overall, the first half of 2025 saw mainly consolidation and recovery, followed by a significant rise after August 2025, and it remained at a high level at the beginning of 2026. This trend indicates that while short-term fluctuations are influenced by sentiment and policy, there are still identifiable cyclical trends, laying a practical foundation for using historical windows in LSTM to extract long-term dependencies.

Table 2 presents the economic meanings of the core variables in the short-term forecasting model presented in this paper. Combining price, yield, trading volume, and technical indicators allows the model to detect changes in trends, the degree of volatility, and market activity. The closer the variable design is to market mechanisms, the more stable the LSTM's identification of key time points will be, which is one of the foundations for improving out-of-sample forecasting capabilities.

Table 1. Monthly Closing Points and Changes of the Shanghai Composite Index during the Sample Period

Month	Close	Monthly Return (%)
2025-01	3250.60	-3.02
2025-02	3320.90	2.16
2025-03	3335.75	0.45
2025-04	3279.03	-1.70
2025-05	3347.49	2.09
2025-06	3444.43	2.90
2025-08	3857.93	7.97
2025-11	3888.60	-1.67
2025-12	3968.84	2.06
2026-01	4117.95	3.76
2026-02	4162.88	1.09

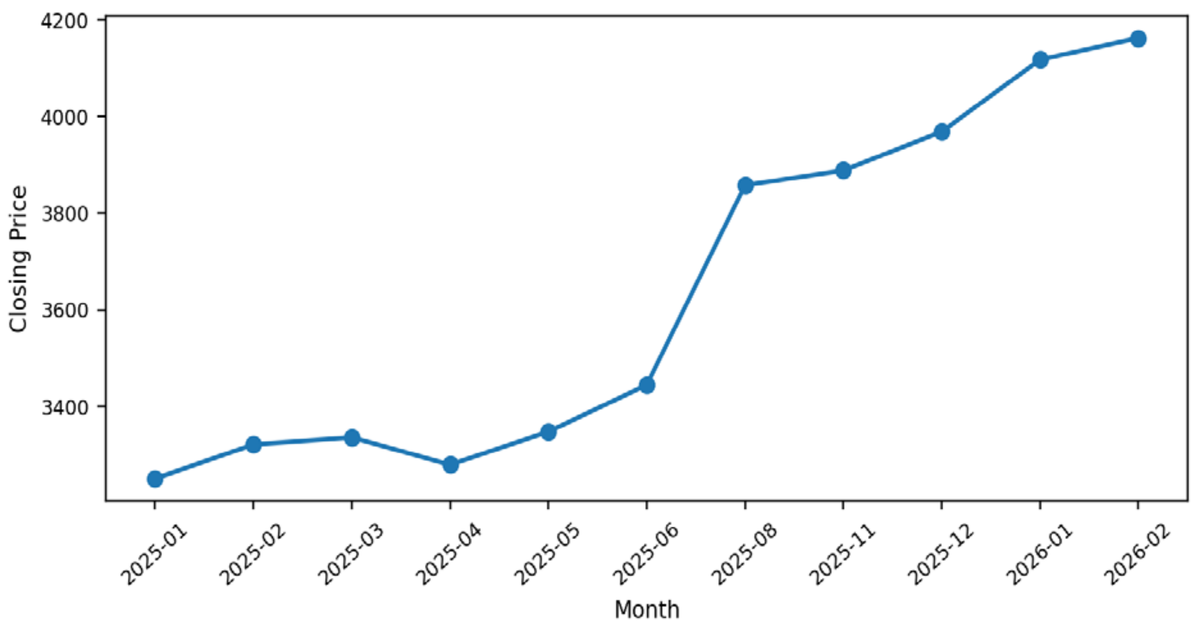

Figure 1. Monthly closing price trend of the Shanghai Composite Index during the sample period.

Table 2. Design of core variables in the short-term forecasting framework

Variable	Meaning	Role	Type
Close	Index closing price	Trend anchor	Input
Return	Monthly change ratio	Volatility signal	Input
Volume	Trading activity	Liquidity proxy	Input
MA / RSI	Technical indicators	Momentum filter	Input
y_hat	Predicted next-step movement	Forecast output	Output

When the research objective is primarily to train a model by minimizing the prediction error of points or yields, mean squared error can be used as the objective function.

$$\mathrm{MSE} = (1/n) * \mathrm{sum}(yi - \mathrm{yhat\_i})\hat{}2 \tag{5}$$

In equation (5), y_i is the actual value, ŷ_i is the predicted value, and n is the number of samples. The smaller the MSE, the more accurately the model fits short-term fluctuations. However, it is still necessary to consider the directional accuracy and risk indicators together to make a comprehensive judgment.

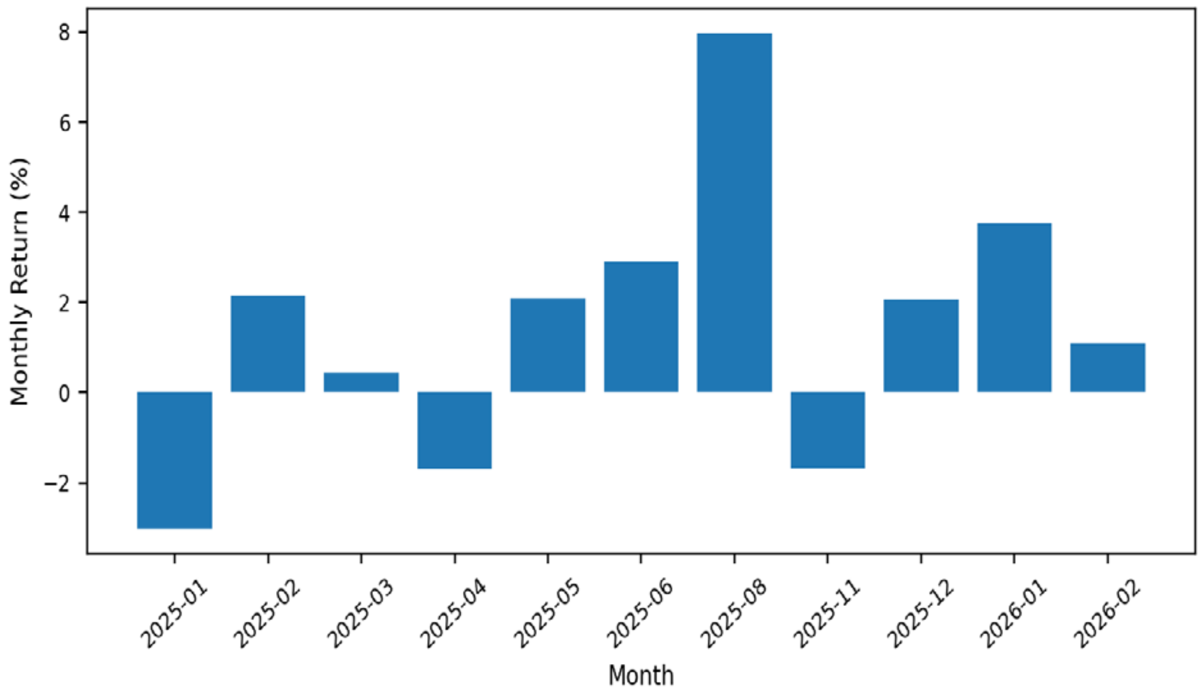

Figure 2. Monthly Gain/Loss Distribution of the Shanghai Composite Index during the Sample Period

Figure 2 shows the dispersion of the monthly gains and losses. The largest increase was in August 2025, reaching 7.97%, indicating a significant resonance between market sentiment and capital flows at a certain point. Negative returns occurred in January, April, and November 2025, demonstrating that the index did not rise linearly. The alternation of positive and negative returns makes the sample highly noisy and non-stationary, highlighting the necessity of incorporating gating structures and dynamic weight allocation.

Table 3. Representative conclusions of relevant English studies in the past three years

Ref	Model	Market	Main finding
[1]	ARIMA-LSTM	Shanghai Composite	Hybrid model improves error metrics
[2]	Attention-LSTM	Stock prices	Better robustness under noisy data
[3]	Bi-LSTM hybrid	Global indices	Real-time forecasting becomes feasible
[6]	M-A-BiLSTM	US stocks	Attention improves predictive accuracy
[8]	Att-LSTM + loss	Major indices	Directional accuracy is enhanced
[10]	News + LSTM	Taiwan stocks	Text features improve short-term prediction

Table 3 summarizes representative English-language research from the past three years. Generally speaking, the research approach has evolved from the original single LSTM to the current hybrid structures, attention mechanisms, multimodal data, and asymmetric loss functions. This indicates that while increasing the number of network layers can improve prediction performance, it cannot provide sustained improvement. Truly effective improvements come from enhancing feature quality, refining task design, and perfecting the evaluation system.

6. Conclusion

This paper addresses the issue of predicting short-term fluctuations in the Shanghai Composite Index. After reviewing the progress of English-language research over the past three years, and using publicly available monthly statistics from the Shanghai Stock Exchange, a descriptive empirical analysis of the index's phased changes during the sample period is conducted. The study shows that the index generally exhibited an upward trend with fluctuations during the sample period, but the distribution of monthly returns was relatively dispersed, indicating that short-term fluctuations in the index included both trend continuation and localized abrupt changes. Traditional linear models cannot fully reflect this complex structure; LSTM, with its gating mechanism, can better capture time-series dependencies and nonlinear information.

The above analysis shows that it is difficult to conduct high-quality short-term forecasting research using only basic price series. Future research should focus on improving the model structure in areas such as multi-source feature fusion, rolling validation, attention interpretation, asymmetric loss design, and risk constraint embedding. Especially when China's capital market is highly sensitive to policy changes and experiences rapid emotional shocks, incorporating technical indicators, capital flow variables, and textual sentiment information into the LSTM model will improve its ability to identify inflection points and abnormal fluctuations.

Overall, LSTM is not a panacea, but its methodological advantages are quite evident in predicting short-term fluctuations of the Shanghai Composite Index. Only by linking the capabilities of deep learning with an understanding of financial market mechanisms, and creating a predictive system that can be explained, verified, and constrained, can the model evolve from a one-sided academic fit into a more practical market analysis tool.

References

[1] *Truong, T. H. (2025). Research on the Application of Digital Healthcare Platforms in Chronic Disease Management. Advances in Computer and Communication, 6(5).*

[2] *Ye, J. (2025). Optimization and Application of Gesture Classification Algorithm Based on EMG. Journal of Computer, Signal, and System Research, 2(5), 41-47.*

[3] *Ye, J. (2025). Design of a Non-Invasive Brain Computer Interface System for Handwritten Text Based on L2 Regularization and Attention Supervision Paradigm, and Optimization of EEG Signal Decoding. International Journal of Big Data Intelligent Technology, 2025, 6 (1), 126, 134.*

[4] *Yin, J. (2026). Research on a CLO Secondary Market Spread Volatility Prediction Model Based on RoBERTa Sentiment Factors. Advances in Computer and Communication, 7(1).*

[5] *Liu, H. (2025). Research on the Evaluation of User Safety Intervention Measures Based on Causal Inference. Engineering Advances, 5(4).*

[6] *Wang, B. (2025). Methods of Load Optimization for Computer Systems Based on Physical Principles.*

[7] *Wang, B. (2025). Application of Efficient Load Test Strategies in Infrastructure. Journal of Computer, Signal, and System Research, 2(4), 69-75.*

[8] *Wu, W. (2025, June). Construction and optimization of intelligent gateway software management platform based on jenkins cluster management under cloud edge integration architecture in industrial internet of things. In International Conference on 6G Communications Networking and Signal Processing (pp. 633-645). Singapore: Springer Nature Singapore.*

[9] *Qi, Y. (2025, October). Research on Privacy Protection of AI Models in Big Data Using Differential Privacy Technology. In 2025 2nd International Conference on Software, Systems and Information Technology (SSITCON) (pp. 1-5). IEEE.*

[10] *Hua, X. (2024, November). Design and Implementation of a Game QoE Monitoring and Evaluation System Driven by Network Traffic Analysis. In International Conference on Cognitive based Information Processing and Applications (pp. 149-161). Singapore: Springer Nature Singapore.*

[11] *Huang, J. (2025, August). Research on Multi-Model Fusion Machine Learning Demand Intelligent Forecasting System in Cloud Computing Environment. In 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS) (pp. 1-7). IEEE.*

[12] *Huang, J. (2025, September). Performance Evaluation Index System and Engineering Best Practice of Production-Level Time Series Machine Learning System. In 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT) (pp. 01-07). IEEE.*

[13] *Zhou, Y. (2024, November). Construction of a Multi-factor Quantitative Stock Selection System for the New Energy Industry Based on Microservices Architecture and Machine Learning Components. In International Conference on Cognitive based Information Processing and Applications (pp. 163-174). Singapore: Springer Nature Singapore.*

[14] *Sun, Q. (2026). Research on a Robotic Natural Language Intelligent Decision-Making Framework Based on Large Language Models, Thinking Chain Reasoning, and Multi-Agent Collaboration.*

[15] *Liu, H. (2026). Research on the Application of Causal Reasoning Method in Content Compliance Experimental Evaluation.*

[16] Yu, X. (2026). Strategy Models and Practical Research of Growth Marketing under the Background of Digital Transformation.
[17] Yin, J. (2026). Research on Financial Time Series Prediction and Multiscale Correlation Based on the Fusion of Network Big Data and Deep Learning.
[18] Hou, Y. (2026). Research on Server Performance Stability Assurance Mechanisms during Cross-Generation Computing Platform Upgrades.
[19] Han, X. (2026). Research on Process Decision-Making Behavior under Incomplete Information Conditions in Automobile Manufacturing Systems.
[20] Yu, X. (2026). Exploration of Multi-Channel Conversion Path Optimization Methods Based on A/B Testing.
[21] Zheng, H. (2026). Research on Edge Computing Deep Neural Network Task Unloading Based on Resource Collaboration Framework and Multi Strategy Optimization.
[22] Zhang, Z. (2026). Research on the Design of Scalable Enterprise-Level AI Systems Data Platform Architectures from an SDE Perspective.
[23] Xiao Ma. Engineering Study of Disaster Recovery and Fault Self-Healing Mechanisms for Distributed Systems under Cross-Regional Deployment Conditions. International Journal of Engineering Technology and Construction (2026), Vol. 7, Issue 1: 1-7.
[24] Zinuo Wang. Value Reassessment Logic of Resource-Based Enterprises in the Context of Energy Transition. International Journal of Social Sciences and Economic Management (2026), Vol. 7, Issue 1: 141-149.
[25] Weiyao Ma. Automated Operation Approach for Scalable Cloud Data Platform. International Journal of Big Data Intelligent Technology (2026), Vol. 7, Issue 1: 131-139.
[26] Zelin Wang. Data Analysis and Risk in Supply Chain Management. International Journal of Social Sciences and Economic Management (2026), Vol. 7, Issue 1: 132-140.
[27] Wang, B. (2025). Research on Load Balancing Technology in Distributed System Architecture. International Journal of Multimedia Computing (2025), 6(1), 152-159.
[28] Liu, H. (2025). Research on the Application of Sentiment Analysis in Customer Segmentation and Precision Marketing. Advances in Computer and Communication, 6(4).
[29] Hong, Y. (2025). Architecture Design and Performance Optimization of a Large-scale Online Simulation Platform for Business Decision-making. Advances in Computer and Communication, 6(4).
[30] Ye, J. (2025). Challenges and Future Development of Neural Signal Decoding and Brain-Computer Interface Technology. Journal of Medicine and Life Sciences, 1(3), 54-60.