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Financial Crisis Prediction Model of Listed Companies Based on Financial Network Indicators

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Abstract. As the information technology industry rapidly advances, ensuring the accuracy and timeliness of financial crisis predictions for listed companies has become progressively more crucial. Traditional prediction models mainly rely on internal financial indicators, which fail to fully reflect the systemic risks of companies in complex market environments. To address this issue, the study proposes a financial crisis prediction model for information technology listed companies by integrating financial network indicators. The model constructs a financial network using company stock returns, extracts network indicators such as degree centrality, eigenvector centrality, betweenness centrality, and pagerank, and combines these indicators with traditional financial metrics. A Logistic model is introduced for optimization. The experimental results indicate that the fusion model achieves a prediction accuracy of 93.2%, marking a notable improvement over the 82.5% accuracy of the traditional Logistic model, and consistently surpassing 92% in several trials. In practical application validation, the model consistently maintains a prediction accuracy above 90% across different industry segments, with a lead time of 8.5 weeks and a response time of only 42 milliseconds. The false positive rate and under-reporting rate are reduced to 3.2% and 2.8%, respectively. The study provides a more precise technical solution for financial risk early warning in information technology companies and has significant practical implications for improving corporate risk management.

Keywords: financial network indicators, listed companies, stock returns, financial crisis, risk prediction

1 Introduction

As the digital economy continues to expand, the information technology sector has emerged as a crucial driver of economic transformation and technological advancement. However, these companies generally have characteristics such as high research and development investments and large cash flow fluctuations, making them vulnerable to market changes and disruptions in the capital chain, which can lead to financial crises [1-2]. Therefore, effectively predicting crises and helping companies take proactive measures to mitigate risks has become an important issue in corporate management. Traditional financial crisis prediction models primarily rely on financial statement data to build statistical models. This approach depends solely on internal financial indicators, making it difficult to comprehensively depict a company's interconnections and systemic risks in a complex market environment [3]. In recent years, financial network analysis methods have shown promising application prospects in financial crisis prediction. By depicting the capital flows and investment relationships between companies, these methods reveal potential links and risk transmission mechanisms. Network indicators, as one of the key features of financial networks, can quantify a company's position within the financial system, providing a new perspective for identifying and predicting potential financial crises [4-5]. Motivated by the need to bridge the gap between internal financial analysis and systemic market risk characterization, this study focuses on listed companies in the information technology sector and introduces an innovative financial crisis prediction model based on financial network indicators. It constructs a financial network using the stock returns of these companies, extracts network indicators that capture systemic risks, and incorporates these indicators as features to optimize a Logistic model. The study aims to enhance traditional models' ability to characterize external connections and provides a new theoretical framework for financial crisis prediction, as well as scientific basis and guidance for risk management in information technology listed companies.

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The remainder of this paper is organized as follows. Section 2 reviews related works on financial crisis prediction models and network indicator applications. Section 3 details the construction of the financial network and the proposed fusion prediction model. Section 4 presents the experimental validation and practical application results. Section 5 concludes the study and discusses directions for future research.

2 Related Works

In recent years, financial crisis prediction for listed companies has gradually become an important research direction in corporate management. As market competition intensifies and the economic environment becomes more complex, scholars both domestically and internationally have proposed various prediction models based on the unique financial characteristics of listed companies. Li's research team found that the root cause of many company bankruptcies lay in the failure to address early financial issues. Therefore, the team constructed a financial early warning model based on an optimized backpropagation neural network. Experimental results showed that the prediction accuracy of the model exceeded 80%, proving its effectiveness [6]. Cao et al. focused on the financial risks of e-commerce listed companies, developing a financial early warning model and financial risk early warning mechanism based on deep learning algorithms. Experimental results indicated that the model could timely diagnose crisis signals and effectively prevent and resolve potential risks [7]. Shang and other scholars used Internet of Things big data technology to improve financial data management, selecting multiple key financial indicators to build a model for predicting company financial risks, achieving significant results [8]. Ding tackled the challenges of heavy workloads and inefficiency in traditional prediction methods by integrating intelligent computation into financial market forecasting, developing a risk early warning and real-time monitoring model based on fuzzy theory. The results demonstrated that the model could more accurately identify potential and explicit risks in financial companies, effectively enhancing the safety and efficiency of company financial management [9]. In addition, Zhu and Li proposed improving the traditional Z-score model using Internet of Things technology to develop a new financial risk early warning system. Their study showed that this method significantly reduced the likelihood of financial crises occurring in Internet of Things companies [10].

On the other hand, network indicators have gained widespread application in financial market research in recent years as important tools for analyzing complex systems. Constructing network indicators by quantifying network structural features provides a new method for analyzing the relationships between different entities in the market and the overall risk characteristics. Rakshit et al. developed a comprehensive social network marketing indicator framework for small and medium-sized companies, combining behavioral reasoning theory and marketing accountability theory, which had a positive impact on the development of these companies [11]. Zhao's research team pointed out that existing studies only focus on simple relationships between affiliated companies, failing to simulate the complex relationships between listed companies in the real financial market. To address this, the team constructed a more comprehensive market network indicator framework, including dual-type entities such as listed companies and their affiliated executives, and a hybrid network of explicit and implicit relationships, improving the depiction of market complexity [12]. Hou et al. discovered that the common trends between stocks are crucial for predicting stock fluctuations. Therefore, they proposed extracting connections between stocks using network indicators and constructed a prediction model using long short-term memory networks. Experimental results showed that the model performed excellently in capturing spatial and temporal signals, achieving significant improvements over traditional methods [13]. Chen et al. developed a dynamic model to study systemic risks in the banking network, analyzing the dynamic changes in bank defaults. They found that the occurrence of financial crises is closely related to the distribution of liquid assets in the banking system and quantified the banks' financial conditions using network indicators [14]. Ferreira et al. constructed network indicators using detrended cross-correlation analysis to study the connectivity of 13 stock markets from 1998 to 2019, proposing time-varying suggestions and revealing the evolving patterns of market connections over time [15].

In summary, existing research has made notable progress in financial crisis prediction, yet several limitations remain. First, most studies rely exclusively on internal financial statement data [6-10], which fails to capture the systemic and contagion risks arising from inter-firm market linkages. Second, while network-based approaches have been applied to stock market analysis and banking risk [13-15], their integration into financial crisis prediction for industry-specific listed companies remains underexplored. Third, prior models combining machine learning with financial indicators [7, 9] generally lack mechanisms to quantify a firm's structural position within

the broader financial ecosystem. In contrast, the present study constructs a firm-level financial network based on stock return co-movements specific to the information technology sector, extracts four network centrality indicators to capture both local and global structural roles, and integrates these with traditional financial features within a regularized Logistic framework. This design directly addresses the gap between internal financial analysis and systemic market risk characterization, offering a more comprehensive and industry-adapted approach to financial crisis prediction.

3 Financial Network Crisis Prediction Model Construction for Information Technology Listed Companies

3.1 Financial Network Construction based on Stock Returns

In the current capital markets, the rapid growth of the information technology industry and the increasing specialization within the industrial chain have led to the formation of complex relationships among companies in the sector [16]. This highly networked feature makes the financial network a key factor in predicting financial crises for listed companies. By studying the market interconnectivity and external risk transmission pathways between companies, financial networks offer a new perspective for financial crisis prediction. They reveal potential risk aggregation points, providing important informational dimensions for the timely identification of crises. The relational network within the information technology industry is shown in Fig. 1.

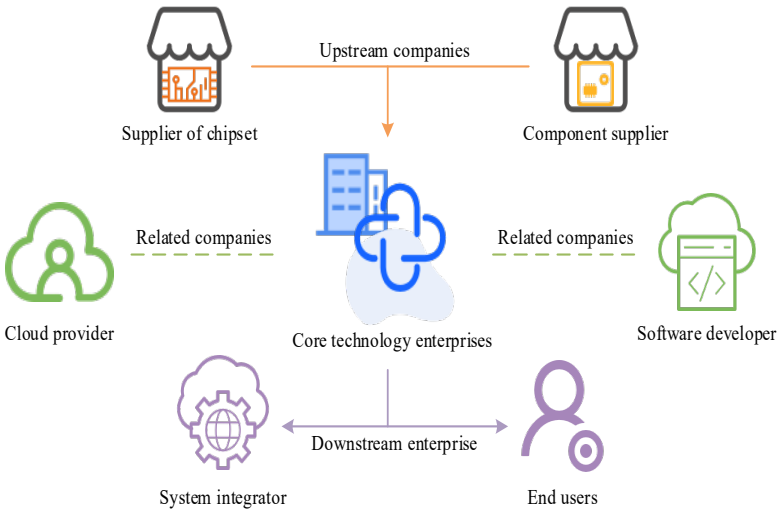


Fig. 1. Information technology industry affiliate network

As shown in Fig. 1, upstream core component suppliers, such as chip and electronic component manufacturers, establish connections with original equipment manufacturers through product supply. Downstream, system integrators transmit products and services to end users. This multidimensional relational network closely links the business conditions and development prospects of companies. This is not only reflected in the frequency of business interactions but also directly in their stock price movements, exhibiting significant correlations [17-18]. Based on this interconnection, the study chooses to construct a financial network through the co-movement of stock returns, capturing the market interlinkages among information technology companies. Stock returns can promptly reflect the business conditions of companies, and the logarithmic return algorithm for company i at time t is shown in Equation (1).

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

In Equation (1), $R_{i,t}$ represents the logarithmic return of company i at time t, while $P_{i,t}$ and $P_{i,t-1}$ are the stock prices of company i at times t and $t-1$, respectively. Logarithmic returns help eliminate differences in the magnitude of price fluctuations, making the return data of different companies comparable. After obtaining the logarithmic return series for each company, the study uses the Pearson correlation coefficient to calculate the correlation between the stock returns of any two companies in order to quantify the market interlinkages among companies. The Pearson correlation coefficient is a statistical tool used to assess the linear relationship between two variables, and its connection to company stock returns is shown in Fig. 2.

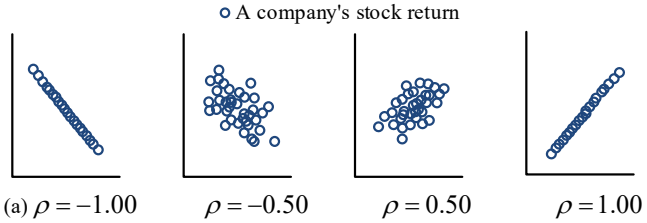


Fig. 2. Pearson's correlation coefficient working schematic

As shown in Fig. 2, the closer the value of the Pearson correlation coefficient is to 1 or -1, the stronger the linear correlation between the stock returns of companies. When the value of the Pearson correlation coefficient is closer to 0, it indicates a weaker correlation between companies, with a smaller impact relationship between their stock returns. The algorithm for the Pearson correlation coefficient is shown in Equation (2).

$$\rho_{ij} = \frac{\sum_{t=1}^{T}(R_{i,t} - \bar{R}_i)(R_{j,i} - \bar{R}_j)}{\sqrt{\sum_{t=1}^{T}(R_{i,t} - \bar{R}_i)^2 \sum_{t=1}^{T}(R_{j,i} - \bar{R}_j)^2}} \tag{2}$$

In Equation (2), ρ_{ij} represents the return correlation between company i and company j, T is the sample size, and $\bar{R}_i$ and $\bar{R}_j$ are the average returns of companies i and j, respectively. Directly using the correlation coefficient to construct the network may introduce random noise, leading to redundant edges in the financial network and affecting the authenticity of the network structure. To improve the reliability of the network, the study removes statistically insignificant edges through significance testing, retaining only the company pairs with significant correlation. The statistical algorithm for the correlation coefficient is shown in Equation (3).

$$t_{i,j} = \rho_{ij}\sqrt{\frac{T-2}{1-\rho^2_{ij}}} \tag{3}$$

When $|t_{ij}| > t_{\alpha/2}(T-2)$ is true, the correlation is considered significant, and the corresponding edge is retained. Here, $t_{\alpha/2}(T-2)$ represents the critical value at the significance level α. The edge selection method effectively reduces noise in the network and highlights the genuine market linkages between companies. In this study, a significance level of $\alpha = 0.5$ was adopted as the threshold for edge retention. The stock return series were computed over a rolling 12-month window, with the network updated annually to reflect evolving market conditions. The edge weight between any two companies was defined as the absolute value of the statistically

significant Pearson correlation coefficient, thereby preserving information on linkage strength while ensuring structural reliability. The weighted adjacency matrix constructed in the study is represented in Equation (4).

$$W_{ij} = \begin{cases} \rho_{ij}, & if \left|t_{ij}\right| > t_{\alpha/2}(T-2) \\ 0, & otherwise \end{cases} \tag{4}$$

In Equation (4), W_{ij} represents the weight of the significant correlation between company i and company j. This method retains the information about the linkage strength between companies while ensuring the statistical significance of the network structure. Based on the construction of the financial network, in order to comprehensively characterize a company's position and role in the network, the study selects four network indicators: degree centrality, eigenvector centrality, betweenness centrality, and pagerank value. These indicators quantify the company's position and role in the network from both local and global perspectives. First, degree centrality measures the direct connection strength of a node, as expressed in Equation (5).

$$D_i = \sum_{j=1}^{N} \left|W_{ij}\right| \tag{5}$$

In Equation (5), D_i represents the degree centrality of node i. A higher value indicates that company i has strong linkages with more companies and is a more active node in the market. In the information technology industry, companies with high centrality are often industry leaders, maintaining close business relations with numerous upstream and downstream companies. Eigenvector centrality further considers the importance of a node's neighbors and can be defined through the eigenvalue Equation, as shown in Equation (6).

$$\lambda_{\mathrm{v}} = w_{\mathrm{v}} \tag{6}$$

In Equation (6), λ represents the largest eigenvalue of the adjacency matrix W, and $\mathbf{v}$ is the corresponding eigenvector. A higher eigenvector centrality indicates that the company is not only important itself but also has strong connections with other significant companies. Betweenness centrality reflects the intermediary role of a node in the network's information or risk transmission process, as shown in Equation (7).

$$B_i = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{7}$$

In Equation (7), σ_{st} represents the total number of shortest paths between nodes s and t, while $\sigma_{st}(i)$ denotes the number of shortest paths passing through node i. Companies with high betweenness centrality often play a crucial bridging role in the transmission of technological innovation or market resources. Their operational performance can influence the stability of the entire industry chain. Finally, the pagerank value, calculated through iterative computation, takes into account both the connection strength and the importance of the connected nodes, as shown in Equation (8).

$$PR_i = \alpha \sum_{j=1}^{N} \frac{W_{ij} PR_j}{D_j} + \frac{1-\alpha}{N} \tag{8}$$

In Equation (8), α represents the damping factor, typically set to 0.85. N is the total number of nodes in the network, and D_j denotes the degree centrality of node j. Companies with a high pagerank value have a significant influence within the entire industry network, and changes in their operational performance may impact other companies through multiple pathways. Based on the above construction process and the calculation of the four centrality indicators, the final financial network structure for information technology companies constructed in this study is shown in Fig. 3.

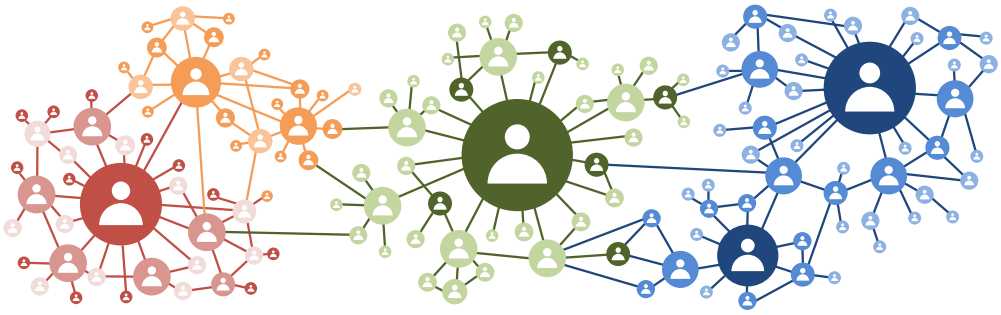


Fig. 3. Financial network structure of information technology industry

In Fig. 3, different colored node clusters represent different company groups, and the node size indicates the centrality indicator values of the companies. The connecting lines represent significant market linkages between companies. This network not only reflects the market linkages between companies but also demonstrates the companies' positions and influence in the network through the size and distribution of the nodes. It reveals implicit information such as the technological dependency and innovation spillover effects between companies, providing important feature dimensions for subsequent financial risk prediction research.

3.2 Construction of Financial Crisis Prediction Model Integrating Financial Network Indicators

Based on the constructed financial network, the study further integrates network indicators into the traditional Logistic model for optimization. Network indicators can reflect a company's position and linkage characteristics in the market, effectively addressing the limitations of the traditional Logistic model and providing a more comprehensive prediction of the financial crisis of listed companies. The Logistic model, as a classical statistical model, maps input features to the probability of an event occurring, combining linear feature relationships with nonlinear probability distributions. It is computationally simple and produces easily interpretable results [19]. The basic principle is shown in Fig. 4.

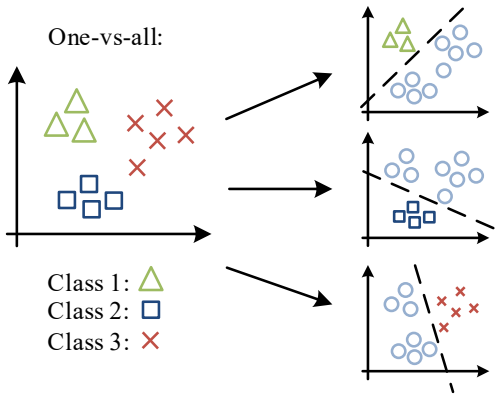


Fig. 4. Logistic regression model basic structure

As shown in Fig. 4, the Logistic model enables a nonlinear mapping of feature variables to probability outputs. In the financial sector, the Logistic model uses a company's financial data as input variables to assess financial health. The model can effectively identify potential crisis companies and provide a quantitative basis for risk management. The algorithm for its conditional probability is shown in Equation (9).

$$P(y_i = 1 | X_i) = \frac{1}{1 + e^{-(\beta_0 + \beta^T X_i)}} \tag{9}$$

In Equation (9), y_i represents the dependent variable, indicating whether company i experiences a financial crisis, β_0 is the intercept, β represents the regression coefficients of financial features, and X_i refers to the financial feature vector of company i, including profitability and other indicators. However, this model only focuses on the company's own financial data and does not account for the company's market linkages or risk transmission within the industry. To more effectively capture these market linkage effects, the study integrates network indicators like degree centrality and betweenness centrality into the Logistic model. By combining traditional financial data, a feature vector that integrates financial and network data is constructed, as shown in Equation (10).

$$X_i = \left[X_i^F, X_i^N \right] \tag{10}$$

In Equation (10), X^F_i represents financial indicators, and X^N_i represents network indicators. The fusion model is able to consider both the company's financial health and its position within the financial network. The prediction formula of the fusion model is shown in Equation (11).

$$P(y_i = 1 | X_i) = \frac{1}{1 + e^{-(\beta_0 + \beta^T X_i^F + \alpha^T X_i^N)}} \tag{11}$$

In Equation (11), $P(y_i = 1|X_i)$ represents the probability of company i experiencing a financial crisis, and α is the regression coefficient for network features, reflecting the impact of network data on financial crisis prediction. Considering that different features have varying degrees of importance for the prediction results, the study further introduces a weighting strategy, optimizing the regression coefficients to assign different weights to each feature. The objective function is expressed as shown in Equation (12).

$$\alpha = \arg\min_{\alpha} \sum_{i=1}^{N} \left[y_i \ln P(y_i = 1 | X_i) + (1 - y_i) \ln(1 - P(y_i = 1 | X_i)) \right] + \lambda \left\| \alpha \right\|_2^2 \tag{12}$$

In Equation (12), λ represents the regularization function, and $||\alpha||_2^2$ is the regularization term used to prevent model overfitting. This approach enables the selection of optimal regression coefficients for both financial and network features, improving prediction accuracy. Additionally, the study uses the clustering coefficient to further optimize the fusion model. Calculating the clustering coefficient helps identify potential high-risk areas in the network, providing essential support for comprehensive risk management [20]. Its working principle is illustrated in Fig. 5.

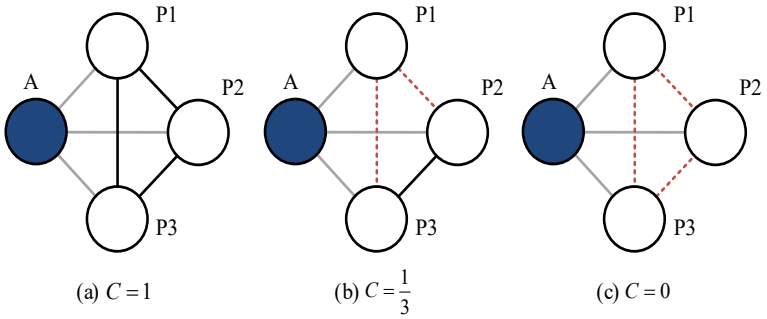


Fig. 5. Cluster factor working principle diagram

From Fig. 5, it can be observed that when a company is connected to multiple neighboring nodes, and the neighboring nodes are also tightly linked to each other, the company's clustering coefficient is higher, indicating that the network group it belongs to exhibits high cohesion. If one of the nodes experiences a financial crisis, it can quickly spread through the dense network structure to the entire group. The clustering coefficient is expressed as shown in Equation (13).

$$C_i = \frac{2E_i}{D_i(D_i - 1)} \tag{13}$$

In Equation (13), C_i represents the clustering coefficient of company i, E_i represents the number of connected node pairs, and D_i represents degree centrality. Additionally, the study also identifies key companies using influence maximization theory. In financial networks, when companies with greater influence experience a financial crisis, it may lead to wider market turbulence. The influence algorithm is shown in Equation (14).

$$I_i \sum_{j \in N(i)} = W_{ij} \cdot P_j \tag{14}$$

In Equation (14), $N(i)$ represents all nodes connected to company i, W_{ij} is the connection strength between company i and company j, and P_j is the crisis propagation probability of company j. Through this approach, the study can identify core companies that may trigger crisis contagion and strengthen risk warnings for these companies. The optimized model objective function is shown in Equation (15).

$$L(\beta, \alpha, \gamma) = -\sum_{i=1}^{N} [y_i \ln P(y_i = 1 | X_i) + (1 - y_i) \ln(1 - P(y_i = 1 | X_i))] + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\gamma\|_2^2 \tag{15}$$

In Equation (15), γ represents the network expansion features, while λ_1 and λ_2 are the regularization coefficients for financial and network features, respectively. Through parameter optimization, the model can balance the contributions of financial data and network data, enhancing the accuracy of financial crisis predictions. The final workflow of the financial crisis prediction model integrating financial network indicators is shown in Fig. 6.

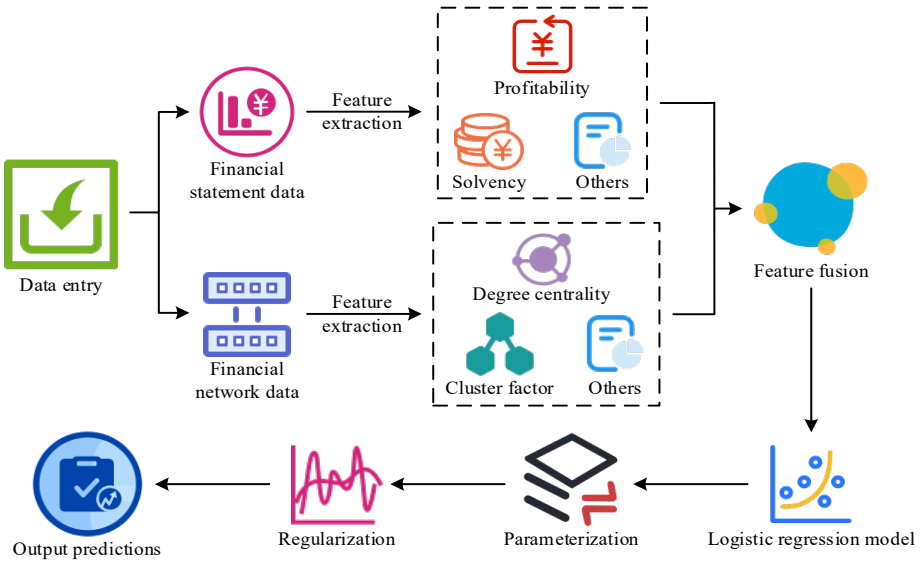


Fig. 6. Financial crisis forecasting model workflow diagram

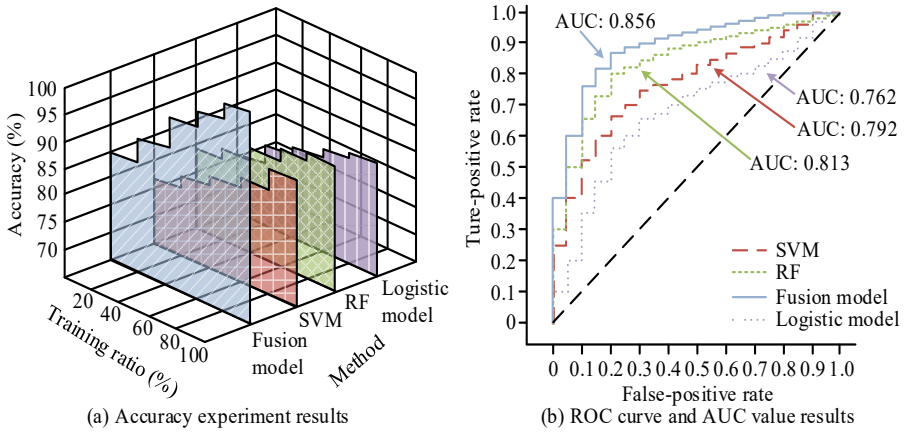
In Fig. 6, the prediction model pipeline consists of four sequential stages: (1) data collection of financial statements and network data; (2) feature extraction, including both traditional financial indicators and network centrality measures; (3) feature fusion via the integrated feature vector defined in Equation (10); and (4) Logistic model inference with regularization-based parameter optimization, yielding the final crisis probability output. These features are then integrated through feature fusion to form a comprehensive feature vector combining both financial and network indicators. Next, the fused indicators are introduced into the Logistic model, and after parameter adjustment and regularization, the final output is the predicted probability of a company experiencing a financial crisis. The financial crisis prediction model that incorporates financial network indicators combines the strengths of traditional financial analysis with the full potential of market linkages reflected in the network features, offering a more thorough analytical approach for predicting corporate financial crises.

4 Performance Validation of Financial Crisis Prediction Model for Information Technology Listed Companies

4.1 Performance Validation of the Financial Crisis Prediction Model

To evaluate the performance of the financial crisis prediction model integrating financial network indicators, the study compared it with the traditional Logistic model, Support Vector Machine (SVM) model, and Random Forest (RF) model. The traditional Logistic model served as the baseline model using only traditional financial indicators, while the SVM model demonstrated excellent performance in handling high-dimensional data and the RF model was applied due to its ability to model nonlinear features; both the SVM and RF models also used the same traditional financial indicator set as the baseline for fair comparison. The proposed fusion model additionally incorporated the four network centrality indicators described in Section 3.1. For parameter settings, the SVM model used a radial basis function kernel with regularization parameter C=1.0, and the RF model was configured with 100 estimators and a maximum depth of 10. The fusion model's regularization coefficients were determined through grid search cross-validation.

The experimental data covered 435 sample companies from China's A-share information technology industry from 2018 to 2022, including 89 crisis companies and 346 non-crisis companies. Sample selection followed three criteria: (1) continuous listing on the Shanghai or Shenzhen exchange throughout the observation period; (2) classification under the information technology sector according to the China Securities Regulatory Commission industry standard; and (3) availability of complete financial statement data. Financial crisis was defined as a company receiving a Special Treatment (ST) designation from the exchange during the observation period, consistent with the prevailing practice in Chinese financial distress research.



(a) Accuracy experiment results (b) ROC curve and AUC value results

Fig. 7. Model prediction accuracy and ROC curve comparison

The dataset was partitioned into training and test sets at a ratio of 8:2. Given the time-series nature of financial data, temporal order was preserved during partitioning, with earlier observations assigned to the training set and later observations reserved for testing, thereby preventing look-ahead bias. Five-fold cross-validation was subsequently applied to the training set, with each fold using a different random seed to ensure the stability and reliability of the evaluation. The experiments were conducted using Python 3.8 and scikit-learn 1.0.2 for model training and evaluation. This study first compared the models based on prediction accuracy and classification performance reflected by the Receiver Operating Characteristic (ROC) curve, and the results are shown in Fig. 7.

As shown in Fig. 7(a), with the increase in the training data ratio, the fusion model consistently maintained the highest prediction accuracy, reaching 93.2% when using the entire training data, significantly outperforming the traditional Logistic model at 82.5%, the SVM model at 84.9%, and the RF model at 86.7%. From the ROC curve in Fig. 7(b), it could be observed that the AUC value of the fusion model reached 0.856, reflecting better classification performance. To more comprehensively evaluate the predictive performance of each model, the study conducted five sets of cross-validation experiments, with each set using different random seeds for data partitioning to ensure the reliability and stability of the results. The experiments recorded the performance of each model in terms of accuracy, recall, and F1 score, and the results are shown in Fig. 8.

As shown in Fig. 8(a), the accuracy of the fusion model consistently remained above 92% across multiple experiments, reaching a maximum of 95.1%. The average recall rate was 92.3%, showing stability across the experiments. From Fig. 8(b), it could be observed that the F1 score of the fusion model was consistently above 90%, significantly higher than the 79%-86% range of the other models, further validating the stability of the fusion model. Next, the study tested the training and prediction runtime of the four models, and the results were shown in Fig. 9.

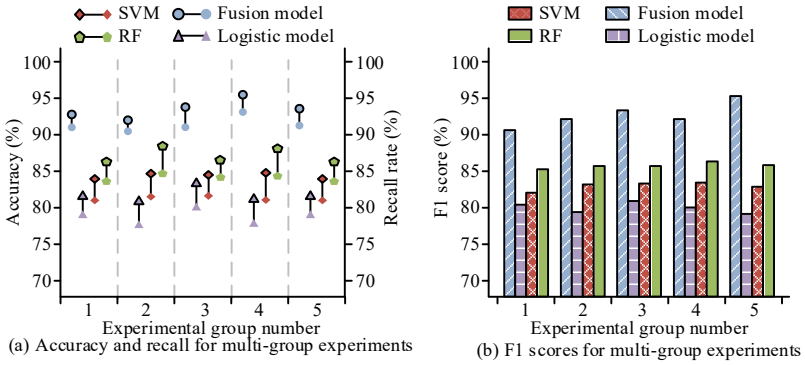


Fig. 8. Accuracy, recall and F1 score results

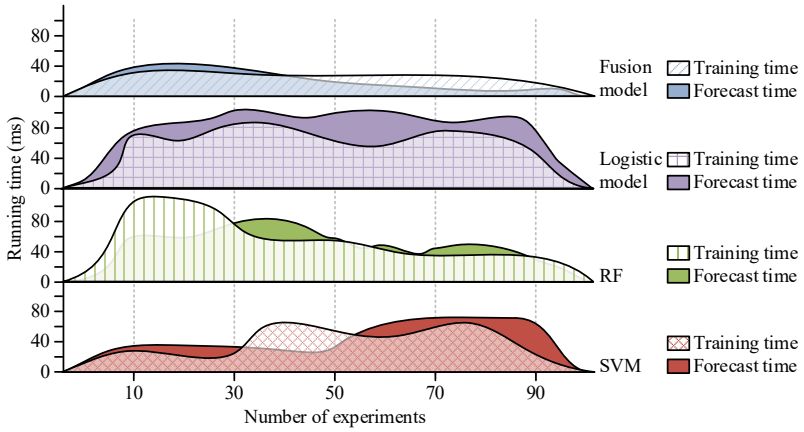


Fig. 9. Training time and prediction time results

As shown in Fig. 9, the fusion model demonstrated a clear advantage in computational efficiency, with the maximum prediction time being only 42 milliseconds, a 57.5% improvement over the traditional Logistic model's 99 milliseconds and a 48.7% improvement over the RF model. Through the performance evaluation, it was found that the prediction model integrating financial network indicators not only performed excellently in terms of prediction accuracy and stability but also exhibited significant advantages in computational efficiency, providing important support for the accurate early warning of financial crises in listed companies.

4.2 Practical Application of the Financial Crisis Prediction Model

After validating the performance of the prediction model, the study further reflected the model's practical value through real-world application experiments. Using 2022 data from technology firms listed on both Shanghai and Shenzhen exchanges, the research implemented real-world crisis warning simulations to evaluate each model's practical effectiveness. By screening publicly available financial reports and market dynamics data, 100 companies were selected as the target test set, with 15 companies experienced a financial crisis during the reporting period. The study first divided the companies in the test set into five categories: software development, hardware manufacturing, cloud services, e-commerce, and information security, and evaluated the financial crisis prediction performance of each model, assessing their adaptability in different business scenarios. The results are shown in Fig. 10.

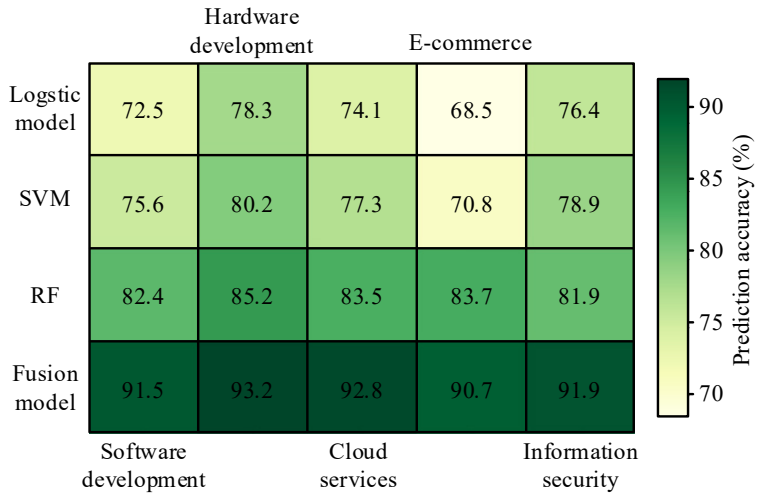


Fig. 10. Prediction accuracy of enterprises in different industries

As shown in Fig. 10, the fusion model maintained a prediction accuracy of over 90% across all industries. The traditional Logistic model, which relied solely on financial features, had the lowest average accuracy at only 73.9%. This indicates that without the support of network indicators, the model struggled to adapt to the varying characteristics of different industries. To comprehensively evaluate the practical application effectiveness of each model, the study conducted a quantitative analysis of model performance from multiple dimensions, including response time and resource occupancy. The study selected two different prediction time points, one month and three months after the company released its public financial report, to test and comprehensively assess the performance across different prediction cycles. Response time was measured as the average wall-clock time elapsed from data input to crisis probability output across 100 repeated predictions on the test set. Early warning lead time was defined as the average number of weeks between the model's first crisis alert and the official ST designation date of confirmed crisis companies. The results are shown in Table 1.

Table 1. Model performance by industry sectors

Metrics	One month after the release of financial data				Three month after the release of financial data			
	Fusion model	Logistic model	SVM	RF	Fusion model	Logistic model	SVM	RF
Response time (ms)	42.5	98.3	156.2	128.7	43.1	99.5	158.4	130.2
Resource occupancy (%)	15.2	12.1	28.4	22.6	15.8	12.4	28.9	23.1
False positive rate (%)	3.2	8.5	6.8	5.4	3.5	8.9	7.1	5.8
Under-reporting rate (%)	2.8	7.2	5.9	4.8	3.0	7.5	6.2	5.0
Early warning (week)	8.5	4.2	5.1	5.8	8.2	4.0	4.8	5.5

As shown in Table 1, the fusion model's response time was reduced by 73.9% compared to the SVM model, which had a response time of 156-158 milliseconds. The average false positive rate and under-reporting rate also remained the lowest among all four models, at only 3.3% and 2.9%, respectively. Additionally, the fusion model excelled in early warning performance, providing a risk warning period of 8.2-8.5 weeks. Finally, the study analyzed the data processing volume and system load during the model's actual operation, evaluating its feasibility in large-scale application scenarios. The experimental results are shown in Fig. 11.

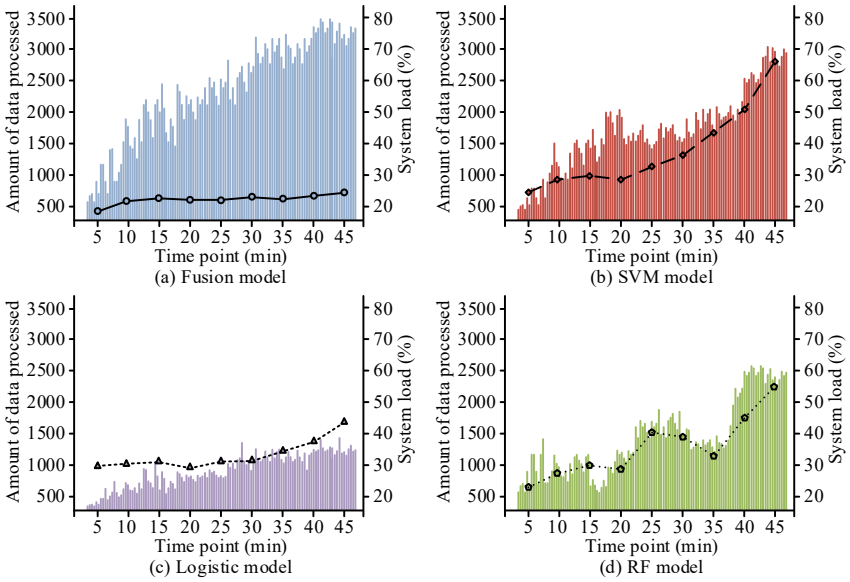


Fig. 11. Graph of data processing volume and system load results

As shown in Fig. 11, with the passage of time, the data processing volume of the fusion model steadily increased, reaching over 3000 data entries within 40 minutes, significantly outpacing the traditional Logistic model and RF model. At the same time, its system load remained stable at around 25%. In contrast, although the SVM model also reached a processing volume of 3000 data entries within 45 minutes, its system load had risen to 67%, indicating higher resource consumption. The experimental results showed that the fusion model demonstrated excellent performance in prediction accuracy, response time, and resource usage. The consistently low false positive and under-reporting rates suggest that the integration of network indicators effectively reduces both over-alerting and missed detection, two critical failure modes in practical early warning systems. The 8.5-week lead time further indicates that the model captures deteriorating network connectivity patterns sufficiently in advance of formal crisis designation, providing actionable windows for managerial intervention. These results collectively confirm the practical viability of the proposed model in real-world financial risk monitoring.

5 Conclusion

To address the issue of insufficient systematic risk identification in the financial crisis prediction of information technology listed companies, the study innovatively proposed a prediction model integrating financial network indicators. By constructing a financial network based on stock returns, extracting network indicators reflecting the company's market connectivity, and combining them with traditional financial features, the model achieved a comprehensive portrayal of a company's financial risk. It not only focused on the internal financial status of the company but also quantified its systemic risk in the market. The experimental results demonstrated that the fusion model significantly outperformed traditional methods in prediction accuracy, stability, and computational efficiency. Specifically, the prediction accuracy reached 93.2%, which was a 10.7% improvement over the traditional Logistic model. The AUC value reached 0.856, reflecting excellent classification performance. In practical applications, the fusion model exhibited strong industry adaptability, with accuracy exceeding 90% in different subfields such as software development and hardware manufacturing. Meanwhile, the model's response time was only 42 milliseconds, 73.9% faster than the SVM model. The false positive rate and under-reporting rate were reduced to 3.2% and 2.8%, respectively, and it could provide up to 8.5 weeks of risk warning time, offering security for companies to formulate early response strategies. Although the study achieved significant progress in model performance and application effects, there is still room for optimization in dealing with sudden market changes and new types of risk features. Future research will further integrate more dimensions of market data to continuously improve the model's prediction accuracy and adaptability, providing more comprehensive decision support for company risk management.

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