A Comparative Study of LSTM and BP Models in Supply Chain Finance Risk Assessment of A-stock Listed Steel Companies

Wenbo Hu *

School of business, University of New South Wales, Sydney, Australia

* Corresponding author: z5562030@ad.unsw.edu.au

Abstract. The iron and steel industry faces the high-risk management challenges in the supply chain finance due to its capital-intensive characteristics and complex supply chain structure. Based on the financial data of 26 iron and steel companies in A-stock, this study uses Long Short-Term Memory (LSTM) neural network and the Back-Propagation (BP) models to assess and compare supply chain finance risks. A multidimensional assessment system covering corporate creditworthiness, supply chain capability, and risk level is established by analyzing the financial data from 2020-2023. The results show that although the LSTM model is good at dealing with long-time series data, the BP model outperforms the LSTM and better fits the actual data when the sample size is small. Therefore, the BP model is preferred when the amount of data is limited, while the LSTM model may perform better when the amount of data increases significantly to improve prediction accuracy and decision support.

Keywords: LSTM, BP, steel industry, financial technology.

1. Introduction

In recent years, supply chain finance has become an important tool to solve the financing problems of China's steel industry, especially for A-stock-listed steel companies. The capital-intensive nature of the steel industry leads to complex and diverse financing needs of enterprises. As a new financing method, supply chain finance can enhance liquidity and optimize capital flow to meet the needs of all participants in this context. As a new financing method, supply chain finance can enhance liquidity and optimize capital flow in this context to meet the needs of each participant. It provides a solution for the steel industry by enhancing liquidity and facilitating capital flow among the participants in the supply chain.

Domestic and foreign scholars have put forward a lot of related theories in this field. Stemmler [1] found that the key feature of supply chain finance is the integration of capital flow into the physical supply chain, and supply chain finance can be described as an important part of supply chain management. Domestic research on supply chain finance started late. Yan Junhong and Xu Xiangqin [2] suggest that supply chain finance involves offering comprehensive financial services through a single enterprise within an industrial supply chain. This can also extend to multiple enterprises operating at various levels of the supply chain, facilitating mutual benefit and coexistence between entities both upstream and downstream. Additionally, it is important to note that supply chain finance is not limited to a single business or product.

In recent years, China's research for supply chain financial risk has also increasing, and different models are used to analyze. Hu Haiqing, Zhang Lang, Zhang Daohong et al [3], and Wu Ran [4] used SVM and SCF-SEIRSD models respectively to analyze the supply chain financial risk of micro, small, and medium-sized enterprises. In addition, different industries have different researchers using different models for analysis. Su Baihao [5] used the Lasso-Logistic model to analyze the supply chain financial risk for companies in the agricultural industry. As for the steel industry, there are also different researchers who mainly used to build Logistic models for analysis, and there are also those who use the TOPSIS method [6-8]. However, there is a lack of comparisons between the different models, and the research data is also mainly focused on the new crown epidemic from 2020 to 2023 Before that, there was a lack of research on the supply chain financial risk of steel companies in this period. Moreover, the logistic regression method requires a large sample size and is not applicable to the data of steel smelting enterprises listed on the A-stock market [9].

In summary, to address the limitations of the Logistic regression method in terms of sample size and prediction accuracy required for the analysis of companies in the steel industry, this paper analyzes the financial data of 26 listed steel companies in the steel industry from 2020 to 2023 by using the Long Short-Term Memory (LSTM) neural network and the Back-Propagation (BP) neural network and conducts a comparative study. This study examines the application of LSTM and BP neural networks in supply chain finance risk prediction of A-share listed steel companies and compares their performance in predicting financial trends and risk factors. The results of the study will provide a reference for model selection, help financial decision-making in the industry, and promote financial stability in the steel industry.

2. Research methodology

2.1. Data collection

This study is based on the financial data of listed companies in China's steel industry between 2020 and 2023, aiming to analyze the financial performance of companies in the industry and their risk propagation in supply chain finance. The data is obtained from the Cathay Pacific database, and the collected data includes major financial statements such as company balance sheets, income statements, cash flow statements, and some key financial indicators such as gearing ratio, working capital turnover ratio, net interest rate, and cash flow position.

In addition, to improve the representativeness and accuracy of the data, this study has screened the companies with complete disclosure of annual reports and open and transparent financial information and will exclude the interference factors of non-recurring gains and losses on financial data. During data processing, appropriate filling and correction measures are taken for missing values and extreme values to ensure data continuity and analytical rigor. These data will provide the basis for subsequent empirical analysis, especially applied to construct a prediction model of supply chain financial risk in the iron and steel industry, which provides reliable data support for analyzing its credit risk propagation path and influencing factors.

2.2. Research Design

(1) Construction of Supply Risk Assessment Indicator System

Although risk assessment can bring benefits, its cost should not be ignored. The pursuit of comprehensiveness and precision may lead to excessive assessment costs, even exceeding the benefits, thus making the risk assessment itself meaningless. Supply chain finance faces a variety of risk factors, so it is necessary to select key indicators and present the real situation in a concise system. When establishing a risk assessment system for supply chain finance, the principles of scientificity, rationality, and relevance should be followed. In this paper, we refer to the basic framework of traditional risk assessment [10, 11]), and combine the subject characteristics and business processes of supply chain finance to design the applicable assessment indicators. The establishment of assessment indicators is mainly based on the following aspects:

Enterprise supply chain capability, which comprehensively reflects the enterprise's dependence on customer and supplier resources, and reveals the risk of concentration of revenue sources and procurement expenditures in the supply chain. Higher levels of concentration may increase the risk of supply chain disruptions due to single-point problems.

Corporate creditworthiness, i.e., indicators related to credit rating, profitability, and solvency, comprehensively assesses the creditworthiness of iron and steel smelting enterprises. Credit level directly affects an enterprise's financing ability, supply chain stability, and market competitiveness. The steel industry has a high demand for capital, and companies with strong credit capacity can usually obtain lower-cost financing and optimize supply chain stability, thereby enhancing their market position.

Risk level, through indicators such as accounts receivable turnover days, inventory turnover days, and capital intensity, reveals the risk of steel enterprises in terms of capital liquidity and asset management. These indicators reflect the efficiency of capital recovery, the level of inventory management, and the degree of dependence on fixed assets, which is an important basis for optimizing the enterprise's financial structure and risk management.

Meanwhile, by using the gradient enhancement model and analyzing the credit rating as the prediction target, the most critical 10 indicators and their weights are obtained, as shown in Fig.1. Among them, accounts payable turnover has the highest weight, followed by total corporate assets, while current ratio and capital intensity have the least weight.

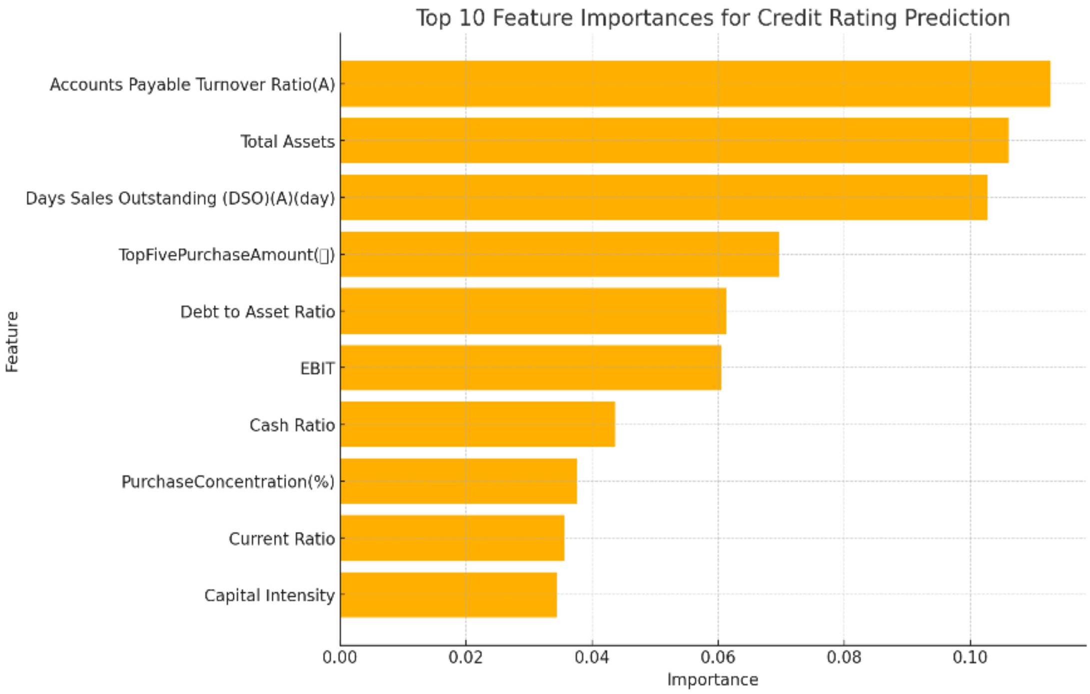

Figure 1. Top 10 key indicators and their weights

(2) Data processing

The credit rating is selected as a qualitative indicator, in which AAA is a full score and assigned 5 points, AA+ is assigned 4 points and AA is assigned 3 points. The remaining indicators are quantitative indicators. At the same time, to further meet the input requirements of the BP and LSTM models, the selected training samples are to be standardized, and through the standardization of the indicators, the attribute data can be transformed into dimensionless data, which is conducive to uniform measurement. The most used standardization processing method is the maximum-minimum value method, which is processed as follows.

$$x_i' = \frac{x_i - MIN(X)}{MAN(X) - MIN(X)}$$

Where x_i is the ith individual in sample X, $MAN(X)$ and $MIN(X)$ are the maximum and minimum values in sample X, respectively, and x_i' is the transformed sample individual.

After building the time series dataset, the following array is obtained which can be used for training BP and LSTM models: [5 rows × 6 columns]; (69, 1, 20) (69, 20) (700, 1, 1) (700, 1) (69, 1, 6) (69, 6).

3. Results

After being analyzed using BP and LSTM models respectively, three plots of prediction results for each group and two groups corresponding to the corporate creditworthiness, corporate supply chain capability, and risk level of 26 A-stock listed steel companies can be obtained respectively.

3.1. Prediction group based on the LSTM model

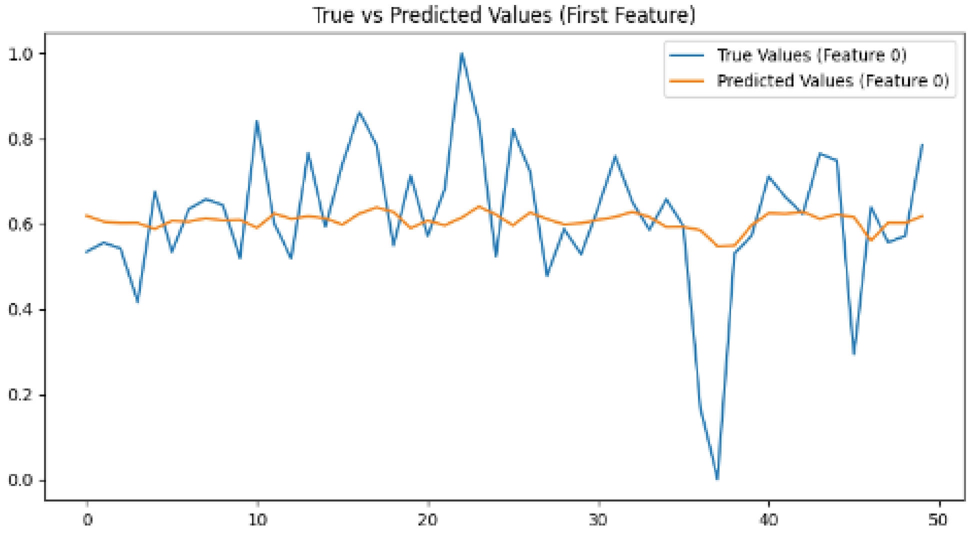

Figure 2. Prediction of corporate creditworthiness

Fig.2 demonstrates the comparison between the true and predicted values of the LSTM model for the first feature. As can be seen from the figure, the true values (blue line) show significant fluctuations, while the predicted values (orange line) are smoother. In most cases, the predicted values of the LSTM model fail to fully capture the dramatic fluctuations of the true values, especially when there are peaks or troughs, and the model often underestimates or overestimates.

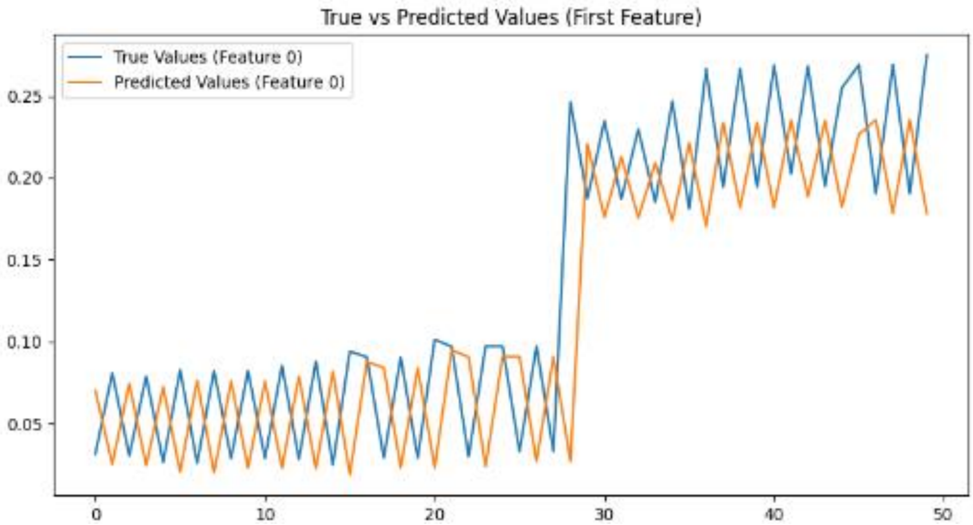

Figure 3. Enterprise supply chain capability prediction

Fig.3 demonstrates the comparison between the predicted and true values of the LSTM model for the first feature. As can be seen from the figure, the true value (blue curve) stays relatively low with small fluctuations for the first 20-time steps, but shows a significant jump around the 25th time step and then fluctuates at a higher level. The predicted values (orange curve), on the other hand, also reflect this trend but remain relatively flat after the jump change. It can be observed that, first, underestimation, i.e., the model's predicted values are generally lower than the true values during the initial phase of the dramatic rise, failing to fully capture the magnitude of the jump. Second, overestimation and lag, in the high volatility region after the jump, the model tracks the true value with some lag and overestimation occurs in the peak portion of the wave.

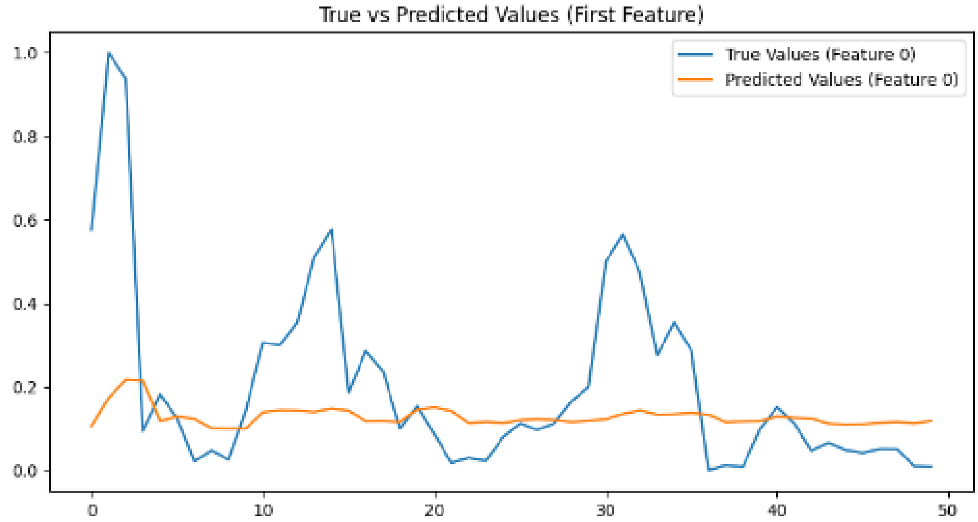

Figure 4. Prediction of enterprise risk level

Fig.4 shows the comparison between the predicted and true values of the LSTM model for the first feature. As can be seen from the figure, the true value (blue curve) shows a sharp increase in the first few steps, followed by a rapid decrease and irregular fluctuations in the subsequent steps. The predicted value (orange curve) is relatively smooth and fails to reflect the sharp fluctuations in the true value. The following phenomena can be observed. Significant underestimation, in the initial stage, the true value rises rapidly to the peak and then falls sharply, however, the predicted value of the model performs smoothly in this stage and fails to capture the sharp change, resulting in significant underestimation. Under volatility, in the subsequent volatility region, the model's predicted value remains smooth and fails to reflect the volatility trend of the true value. This situation suggests that the model is not capable of recognizing the peaks and valleys.

3.2. Prediction group based on the BP model

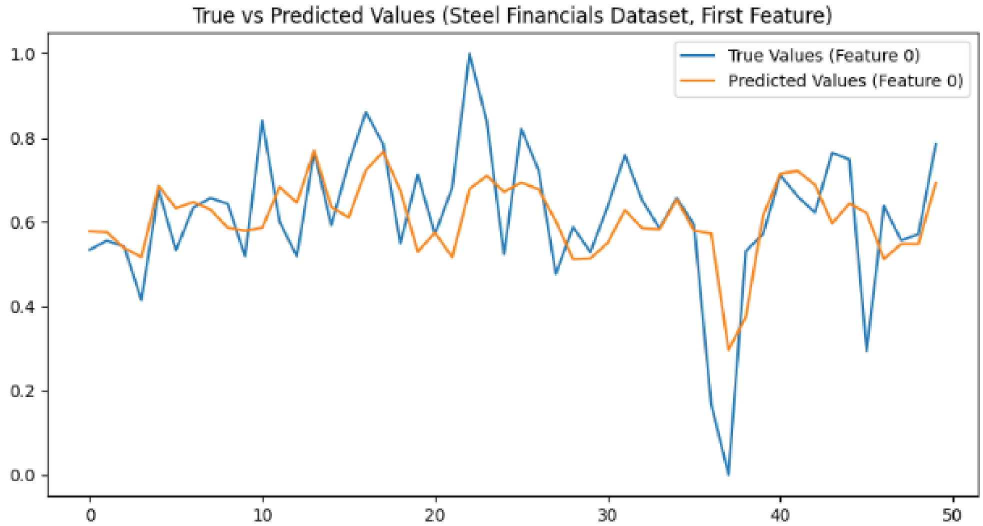

Figure 5. Prediction of Enterprise Credit Capacity

As can be seen in Fig.5, the true value (blue curve) shows large fluctuations, while the predicted value (orange curve) of the BP model is closer to the true value in certain fluctuation regions, but still appears to be relatively smooth overall. Especially in the peak and valley regions, the model fails to follow the fluctuation of the true value completely, and some overestimation or underestimation occurs. This indicates that although the BP model can capture the trend of the data to a certain extent, it still has limitations where there are drastic fluctuations.

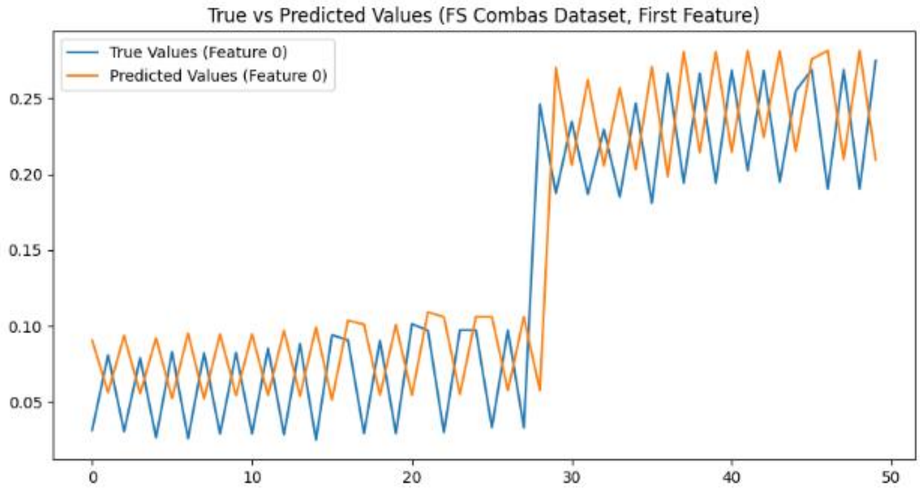

Figure 6. Prediction of Corporate Supply Chain Capability

Fig.6 illustrates that the true value experiences a significant change around the 25th time step. While the predicted value somewhat aligns with this trend, it lags the true value. Additionally, the prediction accuracy diminishes in the high volatility region following the jump. This indicates that the BP model has a certain delay in capturing the fluctuations after a sudden change, and although it can reflect the main trend, the adaptability to the fluctuation amplitude is relatively weak.

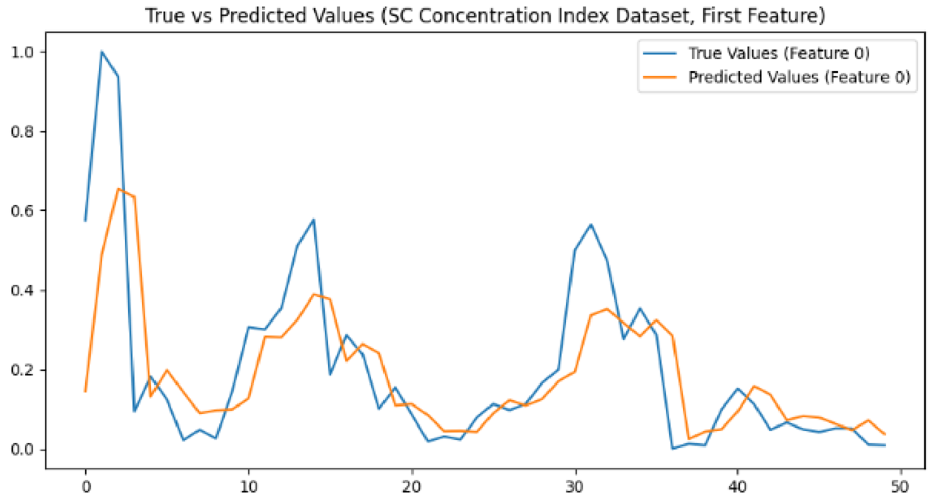

Figure 7. Prediction of enterprise risk level

Fig.7 demonstrates the prediction effect of the BP model on different datasets. The true values show sharp fluctuations with rapid increases and decreases in the initial period, while the predicted values of the BP model are relatively low and smooth, failing to accurately reflect the initial sharp changes. This discrepancy may be due to the fact that the BP model is less sensitive to high-frequency fluctuations and tends to favor the average trend, thus ignoring extreme changes in the short term. Therefore, the BP model has some limitations in coping with large fluctuations and sudden changes in characteristics, but the prediction effect is more stable in regions with smoother data.

Through comparative analysis, we find that the BP model outperforms the LSTM model in predicting the supply chain financial risk of listed companies in the steel industry with a smaller sample size and shorter time period, and it’s fit to the true value is higher. The LSTM model fails to predict effectively due to the financial data of only 26 A-share listed steel smelting companies (covering only 2020-2023). Therefore, the BP model appears to be more appropriate when analyzing and testing the financial data of A-share steel smelting companies.

This large deviation may stem from the over-smoothing of the LSTM model, which is usually due to the insufficient amount of training data, the short time step setting, and the complexity of the model structure. Specifically, the LSTM model contains six layers of LSTM units, and this complex structure tends to lead to overfitting in the case of small samples, although the model performs well on the training data, it is ineffective in predicting new data. In addition, the time step of the model is set to 1, which means that only the data from the previous time step is used for prediction, which may result in failing to capture the long-term trends and volatility characteristics of the data. For financial data, longer time steps typically better reflect time-series dependencies. Finally, the model uses 30 training rounds and a batch size of 16, which can lead to over-training on small sample data, further increasing the risk of overfitting.

4. Conclusion

In this study, based on the financial data of 26 steel companies in A-stock from 2020 to 2023, a multidimensional assessment system of corporate creditworthiness, supply chain capability, and risk level was constructed, and LSTM and BP neural network models were used to conduct a comparative analysis of supply chain financial risk. The results show that although the LSTM model has advantages in dealing with long time series data, it is prone to overfitting under small sample size, difficult to effectively capture the dramatic fluctuations in the data, and has a smoother prediction effect. The BP model, on the other hand, outperforms the LSTM in small samples and is able to more accurately fit the fluctuations in the actual data, especially in the peak and valley regions, where the performance is more stable. Therefore, the BP model is more applicable in the case of limited data volume, while the LSTM model may provide higher prediction accuracy in the condition of sufficient data volume.

Future research should validate the applicability of the two models by expanding the sample size and time span. Additionally, exploring a hybrid model that combines the two could further improve prediction accuracy. This study offers empirical support for choosing a model to assess supply chain financial risk in the steel industry and serves as a reference for risk management decisions within the sector.

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