

## Research Article

# Risk Prediction Model of Enterprise Financial Data Based upon Sensor Signal Fusion

**Hua Jiang** 

*Xing Zhi College of Xi'an University of Finance and Economics, Xi'an 710000, Shaanxi, China*

Correspondence should be addressed to Hua Jiang; [b20160505230@stu.ccsu.edu.cn](mailto:b20160505230@stu.ccsu.edu.cn)

Received 21 March 2022; Accepted 25 April 2022; Published 23 June 2022

Academic Editor: Muhammad Muzammal

Copyright © 2022 Hua Jiang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The prediction of financial distress has always been a topic of concern because it is very important to listed companies, stakeholders, and even a country's economy. This research mainly discusses the risk prediction model of corporate financial data based on sensor signal fusion. This article analyzes the factors that affect financial risks through the study of related theories. Based on the design principles and qualitative analysis of the predictive index system, this paper constructs the financial risk prediction index system of listed companies from five aspects: profitability, solvency, asset management capability, operating capability, and growth capability. And it verifies the applicability of financial indicators through independent sample *t*-test. In order to effectively prevent the occurrence of corporate financial risks, this article takes listed companies as the research object. Starting from multiple angles that affect the occurrence of corporate financial risks, this article constructs a comprehensive and effective financial risk prediction index system for listed companies. And it uses sensor signal fusion algorithm to build an effective financial risk prediction model. Through this model, the enterprise's risk management ability can be effectively improved, the enterprise's risk prevention mechanism can be improved, and it can be successfully applied to the actual management of the enterprise, and the enterprise risk management mechanism can be enhanced. In general, the probability of making a type I error is slightly greater than the probability of making a type II error, but the misjudgment rate is below 25%, which is acceptable. This research provides scientific and effective guidance for corporate finance.

## 1. Introduction

With the capital market falling into a sluggish situation, enterprises' demand for funds continues to grow. At the same time, due to the increase of market risk in the post-financial crisis era, it has increased the difficulty of financing for listed companies, and the probability of corporate operating risks has increased. At the same time, as the market environment faced by enterprises becomes more and more complicated, various non-financial indicators produced in the course of business operations have an increasingly important impact on the development of enterprises. It needs to attract the attention of the majority of business managers. In recent years, the speed of international economic development has been at a relatively low level. The economic situation is not very clear, which has affected the vigorous development of the positive economic globalization process. It has brought a devastating blow to many

emerging market countries that rely on export-oriented economies for survival.

At present, in order to ensure the realization of the goals of social attention to modernization in the face of a downturn in the international economic environment, the state helps enterprises to overcome the difficulties brought about by the economic crisis. It adjusts its industrial structure, transforms its economic development mode, and vigorously deepens corporate reforms. As a result, companies will be pushed to the market to face more challenges from market uncertainties. The process from a good business condition to a financial distress is a gradual process of change. Generally speaking, before the crisis, the business conditions of enterprises have deteriorated day by day. It has gone through a process from quantitative change to qualitative change, from gradual change to sudden change. The normality of the financial operation of an enterprise can be reflected in various financial statements issued by the enterprise. Therefore, it is necessary

to monitor these financial indicators at all times and use feasible technical methods to predict the financial status of the enterprise according to the changes of the indicators.

When making financial forecasts for listed companies in the information service industry, we should first find indicators that can reflect the true financial status of the company. Shang et al. believe that, with the integration of big data, Internet of Things, cloud computing, and other concepts and technologies into social life, big data technology can improve corporate financial data processing capabilities. At the same time, with the intensification of competition among enterprises, investors and enterprises pay more attention to the role of financial crisis early warning in enterprise management. They selected a number of financial indicators based on big data mining of the Internet of Things. They found that the rules among all financial indicators choose more representative financial risk indicators. Then they used FCM (fuzzy clustering method), parallel rules, and parallel mining algorithms to determine frequent fuzzy option sets, so as to obtain fuzzy association rules that meet the minimum fuzzy credibility, finally, selecting the relevant data of listed companies to analyze the corporate financial risks, and verifying the method he proposed [1]. The purpose of Bogodistov Y's research is to enhance the existing enterprise risk management (ERM) theory by introducing a resource-based view and a dynamic capability view. These strategic management concepts may solve some theoretical flaws in the field of risk management. The concept of risk management capability is proposed to explain the company's risk elasticity. For illustrative purposes, he cited practical examples. First of all, he provided a framework based on the resource point of view to help determine the priority of risk management. Second, the dynamic capability perspective illustrated how the company handles unforeseen events. Third, he suggested that dynamic capabilities are needed to allow continuous reevaluation of the impact of specific resources, thereby reevaluating ERM priorities. Fourth, risk management capabilities, as a component of dynamic capabilities, enable companies to develop risk resilience in a turbulent environment [2]. Baker et al. investigated working capital management (WCM) practices used by Indian companies listed on the National Stock Exchange (NSE). He used questionnaires, collected data from 110 financial managers, and used various statistical techniques to test statistical significance. The survey results indicate that the majority (54.5%) of the sample companies adopted a modest approach when financing their activities. This involves a trade-off between liquidity and profitability. Respondents tend to use informal methods for WCM and regard accounts receivable management as the most important component of WCM. In terms of WCM monitoring and financial measures, respondents mainly consider the cash conversion cycle and net working capital. Indian companies tend to use centralized cash management and rely heavily on material requirements planning (MRP) and enterprise resource planning (ERP) for proper inventory management. There are no significant differences in tests involving company size, overseas sales, and average age [3]. Paraque aimed to emphasize the necessity of a complete

break with the methodological individualism that dominates the economic and management fields, especially the financial field. He argued that it is necessary to try to understand the problems and methods needed to coordinate economic actions to meet social needs. He questioned methodological individualism and the leading role of shareholders. Treating social welfare only as the result of maximizing shareholder value means not only to fully understand the challenges, but also to innovate in the way of coordinating the actions necessary to meet these challenges. And it may promote another role as a substitute for shareholders [4]. The purpose of D Swagerman et al.'s study was to show an example of the current state of the shared service concept applied to the finance function. Their research stemmed from ongoing research in universities following the current development of financial functions supported by information and communication technology. The rapid development of information and communication technology has led to the combination of new "information economics" and the development of organizational theory, which has had a profound impact on the best way to organize activities. Therefore, the organization is reorganizing, and the boundaries of the organization are changing. These developments are captured by the powerful concept of virtual organization. The concept of shared services can be understood as providing answers to these new organizational economics. Therefore, it is related to the general concept behind the virtual enterprise [5]. The financial reports of different listed companies are very different; even for companies in the same industry, it is difficult to guarantee the same standard to report their financial status. Therefore, when choosing indicators, we must choose the financial indicators that are common among different companies and are generally applicable. At the same time, we must be clear about the meaning of financial indicators and select those financial or nonfinancial indicators that can reflect the characteristics of the information service industry. Therefore, it is necessary to choose financial indicators based on the principle of pertinence. Small- and medium-sized enterprises have become an important force supporting the development of the national economy, and their role is indispensable. However, small- and medium-sized enterprises have their own shortcomings such as small capital scale, backward production technology, single product structure, imperfect financial system, imperfect internal control, unreasonable capital structure, and poor ability to resist risks. The financial risks it faces are extremely high, the bankruptcy rate is very high, and the impact of the financial crisis has brought more SMEs to the brink of life and death.

In the selection of indicators, this article not only incorporates traditional financial indicators into the indicator system, but also includes nonfinancial indicators generated in the course of business operations, including equity structure and corporate governance. In order to effectively avoid unnecessary sample information deficiencies during the discretization of continuous numerical values, the research adopts the neighborhood rough set theory, which has obvious advantages over continuous numerical reduction. Through multiple experiments, the appropriate

neighborhood radius is selected to improve the classification accuracy and finally achieve the purpose of dimensionality reduction and simplify the model structure. In this paper, sensor signal fusion is used in the field of financial crisis early warning. While powerfully expanding the application field of sensor signal fusion, it also enriches and expands enterprise financial crisis early warning models and algorithms. It effectively promotes the effective supervision of corporate financial operations. As the scientific research of intelligent computing, rough set theory has made great progress in both theory and application practice, showing its bright prospects. Rough set theory not only provides new scientific logic and research methods for information science and cognitive science, but also provides effective processing technology for intelligent information processing.

## 2. Enterprise Financial Data Risk Prediction Model

*2.1. The Optimized Implementation of Company Asset Management Based on Sensor Signal Fusion Technology.* By establishing an operational mechanism for optimal implementation of asset management based on the Internet of Things technology, this article discusses how to apply it to asset management. It uses the characteristics of the Internet of Things T to T (Thing to Thing) and H to T (Human to Thing), the characteristics of RFID repeated reading and writing and the use and reading of multiple tags, as well as ZigBee's low power consumption, low complexity, and the feature of multiple deployment nodes. By using cloud computing to share asset data, multiple users of Company M can know the whereabouts of assets and reduce the user's processing burden. The rapid deployment of virtualization technology can reduce the burden of a large influx of users at the same time. It effectively prevents the system from suddenly crashing, and you can use the mobile phone APP to let users know the location and management of assets in any location. Based on the Internet of Things technology, M Company's asset management has been optimized and subdivided into 5 items: Internet of Things to asset management, RFID to asset management, ZigBee to asset management, asset management to cloud computing, and cloud computing to mobile vehicle APP. The following is a specific description [6].

The original definition of the Internet of Things is to connect items to items and people to items through the Internet. And linking the asset management of M company can realize the linking of company M's goods to goods and people to goods. Through the Internet, company M can know the location of the item, the current status of item borrowing, and the item's direct borrowing.

Cloud computing management mobile vehicle APP: M Company's asset management mobile vehicle APP based on Internet of Things technology is like another extension of sharing. It uses M company's asset management action vehicle based on the Internet of Things technology to query the location of assets. M company's financial management personnel do not need to use a computer to query and only need to use their own mobile phones to quickly find them, reducing time waste.

Fund management optimization is as follows:

- (1) In order to establish a scientific, reasonable, and orderly capital transfer mechanism of M Company, it is required to strengthen the unified management, centralized scheduling, and paid use of funds. The company uses internal funds to simulate bank settlement to optimize the financing structure, moderate debt management, and ultimately reduce financing costs and financing risks to a reasonable level.
- (2) Strengthen the management of M company's capital organization and maintain the rationalization of M company's capital composition. More seriously, the problem of concealed guarantees by subsidiaries and blindly asking for money from the head office of M company have been caused. Company M needs to build an efficient and specialized fund management institution to control the use and direction of the funds of Company M. (2) This specialized organization can be subordinate to the organization of the Ministry of Finance, or it can be directly controlled by the board of directors of the M company or the general manager of the M company. This structure needs not only to work with the financial department to effectively monitor the flow of funds and use status of M company, but also to be directly accountable to M company's board of directors or M company's general manager. It regularly reports to the board of directors of company M or the general manager of company M and makes timely adjustments and improvements according to the problems existing in the use of funds of company M [7].
- (3) Strengthen the scientific management of M company's foreign investment: strengthen the scientific management of M company's foreign investment, and do the following specific tasks. First, the market department of M company must work with the financial department to conduct research on the industry's market dynamics and provide effective demonstration reports. Second, before making investment decisions, the financial department of company M must conduct scientific and reasonable calculations and demonstrations on company M's investment projects and report to the board of directors or general manager of company M. Third, after the occurrence of M company's foreign direct investment, the financial department, marketing department, and related auditing departments of M company must regularly evaluate the investment status of the project and strengthen the financial monitoring of the project. On this basis, timely feedback, adjustment, and improvement are carried out according to the project evaluation results and financial monitoring results [8].

Since the electronic energy levels are discrete and not continuous,  $E_2-E_1$  will also be in a discrete state. According to quantum mechanics, the quantized energy level at the

angular frequency  $\omega$  of the harmonic oscillator is as follows [9]:

$$E_n = \left(n + \frac{1}{2}\right)h\omega_M, n = 0, 1, 2, \dots \quad (1)$$

When the quantum harmonic oscillator is at an ambient temperature of  $T$ , the probability  $\rho_n$  of its energy level  $E_n$  is

$$\rho_n = \frac{\exp(-(n+1/2)h\omega_M/k_B T)}{\sum_n^{\infty} \exp(-(n+1/2)h\omega_M/k_B T)} \quad (2)$$

where  $k_B$  is Boltzmann's constant. According to quantum mechanics, the larger the quantum number, the greater the energy required for quantum transition to a higher energy level, and there is a proportional relationship between them. That is, the quantum number of the electron energy level from  $E_n \rightarrow E_{n+1}$  is proportional to the energy. On the contrary, the required energy of the electron energy level from  $E_{n+1} \rightarrow E_n$  is inversely proportional to the quantum number [10]. Then, we can get the Stokes and anti-Stokes intensity factors of  $N$  identical harmonic oscillators at temperature  $T$  as follows:

$$N \sum_{n=0}^{\infty} (\sqrt{n+1})^2 P_n = \frac{N}{1 - \exp(-h\omega_M/k_B T)}, \quad (3)$$

$$N \sum_{n=0}^{\infty} (\sqrt{n})^2 P_n = \frac{N}{\exp(h\omega_M/k_B T) - 1}.$$

The biggest feature of cloud computing is the ability to flexibly adjust the burden of the server. If the server burden is large, virtualization technology can be used to add several virtual servers to reduce the burden. If the server load is small, you can only open a few virtual servers. This is also a feature of the rapid deployment of M company's cloud computing virtualization technology. For asset management, there is also the necessary existence of cloud. Assets will only increase, and the greater the management burden for M company, it also needs a server that can afford huge assets. Sharing is another major feature of cloud computing. Sharing allows people who need to use the asset to know whether the asset is being used. It is like an online platform, allowing everyone to see where the assets are going and whether they can be borrowed on the platform. The intensities of the Stokes and anti-Stokes lines are as follows [11]:

$$I_S = I_0 \left(\frac{l}{\lambda_S}\right)^4 \frac{1}{1 - \exp(-h\omega_M/k_B T)}, \quad (4)$$

$$I_{aS} = I_0 \left(\frac{l}{\lambda_S}\right)^4 \frac{1}{\exp(h\omega_M/k_B T) - 1},$$

where  $l$  is the length and  $I_0$  is the intensity of the incident light. In the digital filter, the stability and linear phase of the filter system are first considered. Because the spectral signal in the point signal is Gauss-like and contains a variety of frequency components, the actual spectral components are in the low frequency range. Assuming that a sinusoidal signal with a frequency of  $\omega$  passes through the filtering

system, in order to ensure that the signal is not distorted, it is required that each frequency component in the sinusoidal signal passes through the filter for the same time. The expression of FIR filter is as follows [12]:

$$y(n) = \sum_{k=0}^{N-1} h(k)x(n-k). \quad (5)$$

The corresponding transfer function of the FIR filter is as follows:

$$H(z) = \sum_{n=0}^{N-1} h(n)z^{-n}. \quad (6)$$

ZigBee two-way wireless communication technology has the characteristics of short distance, low complexity, low power consumption, and low cost. ZigBee technology has star-shaped, tree-shaped, and mesh-shaped network structures and can cover a wide range of networks. So it is possible to increase network nodes and cancel failed nodes. As far as asset management is concerned, since most assets are scattered, the scope of management is very large. By using ZigBee technology to build company M's network structure, it can be distributed on various assets to facilitate inquiries about the whereabouts of assets. The combination of RFID and ZigBee can further improve the Internet of Things. The transmission of ZigBee technology is mainly used for data collection, combined with the RFID system, to attach RFID tags to assets. By using the tag to read the data, it uses the wireless network to transmit the data to the database via the ZigBee node. In this way, the purpose of the Internet of Things of the M company is realized, and the management efficiency of the M company is relatively improved.

The arithmetic expression of cumulative denoising is [13]

$$\bar{y} = \frac{1}{n} \sum_{i=0}^n y_i. \quad (7)$$

The inter-class dispersion matrix is defined as follows:

$$S_B = \sum_{i=1}^c N_i (\mu_i - \bar{\mu})(\mu_i - \bar{\mu})^T. \quad (8)$$

The within-class dispersion matrix is defined as follows [14]:

$$S_W = \sum_{i=1}^c \sum_{\vec{f}_k \in F_i} (\vec{f}_k - \mu_i)(\vec{f}_k - \mu_i)^T. \quad (9)$$

The manifestation of impact failure is

$$y_{\text{out}}(t) = y_{\text{in}}(t) + a\delta(t). \quad (10)$$

In the formula,  $a$  is the sudden change value, and  $\delta(t)$  is the pulse signal at time  $t$  [15]. The expression of the energy  $E$  of the residual signal is

$$E = \int |\delta(k)|^2 dt = \sum_{k=1}^N |\delta(k)|^2. \quad (11)$$

Among them,  $N$  is the number of sampled samples. The expression of the coefficient  $K$  of the residual signal is

$$K = \frac{1}{N} \sum_{k=1}^N \left( \frac{\delta(k) - \bar{\delta}}{\sigma} \right)^4. \quad (12)$$

Among them,  $N$  is the number of samples, the average of the residuals, and the standard deviation [16].

Suppose the decomposition coefficient  $\{d_{j+1,k}^{2n}, d_{j+1,k}^{2n+1}\}$  of  $f(x)$  in subspace  $U_{j+1}^{2n}$  and  $U_{j+1}^{2n+1}$ ; then the reconstruction coefficient in subspace  $U_j^n$  is  $\{d_{j,m}^n\}$ :

$$d_{j,m}^n = \sum_{k \in Z} h_{m-2k} d_{j+1,k}^{2n} + g_{m-2k} d_{j+1,k}^{2n+1}, g_{m-2k} = \sum_{k \in Z} (R + D). \quad (13)$$

The value function or objective function of FCM is defined as follows [17]:

$$J_c = \sum_{i=1}^C \sum_{j=1}^n u_{ji}^m \|x_j - c_i\|^2, 1 \leq m \leq \infty. \quad (14)$$

The error of the algorithm is calculated using offline performance criteria, and the formula is as follows:

$$E_{\text{RMS}} = \frac{\sum_{i=1}^{\text{iter}} \text{fun}(g\text{best}_i)}{\text{iter}}. \quad (15)$$

The node output  $b_j$  of the hidden layer is

$$b_j = \frac{1}{1 + \exp(-\sum_{i=1}^m w_{ij} + \theta_j)} \quad (j = 1, 2, \dots, p). \quad (16)$$

In addition,

$$0 < \theta \leq 1. \quad (17)$$

**Financial Warning Sample Design:** in this study, a certain proportion of financial crisis companies and normal companies are selected as the sample data for the study. In order to facilitate comparative experiments and analysis and research, the selected sample belongs to the same period, the same industry, and the same scale of normal financial (a listed company in the same industry and similar asset size as the company that was ST for the first time in the same period) operations to form a paired sample for analysis. This paper selects a total of 192 ST companies and 200 non-ST companies from 2017 to 2020, and the total number of samples is 392.96 companies that were randomly selected from the ST sample, and 96 companies were randomly selected from the non-ST companies. These 192 companies are used as training samples to construct and train the financial early warning model, and 192 of the remaining samples are also selected as test samples to test the accuracy of the model [18].

Financial crisis early warning indicator system:

- (1) Enterprise benefit level indicator: the ultimate goal of business development is to obtain sufficient profits. The level of profitability of an enterprise directly affects the interests of all employees of the enterprise

and also has an important impact on the ability of the enterprise to repay debts.

- (2) Corporate debt repayment ability measurement index: an important measurement indicator of the corporate financial operation status is the corporate debt repayment ability. If the company cannot repay its debts on time, the possibility of the company's eventual bankruptcy will increase significantly.
- (3) Enterprise operation ability index: the operation ability index of an enterprise is a measure of the ability of an enterprise to operate and develop, that is, the ability of an enterprise to obtain profits in the future. It is an intuitive reflection of the efficiency of enterprise economic resource management and utilization and operation, and it is also an effective reflection of the company's future debt solvency and profitability.
- (4) Other relevant indicators: in addition to the selected indicators, this article also selects other relevant indicators. As in real life, the financial statements of enterprises generally adopt the accrual system. The revision of accounting policies and methods and the subjective factors of financial personnel and business managers will cause the financial statements to be untrue. And the most intuitively reflecting the enterprise's operating conditions and not easily affected by the subjective factors of enterprise managers is the enterprise's cash flow indicator. Therefore, this article focuses on selecting financial indicators that can sensitively reflect the operating conditions of the enterprise. At the same time, in order to be able to fully reflect all the problems faced in the process of business management, this article also selects some nonfinancial indicators that have a significant impact on the maturity of the business. This paper incorporates it into the research field of financial crisis early warning of listed companies [19]. The early warning model development and evaluation is shown in Figure 1.

**2.2. Standardization of Data Samples.** Due to the differences in the industry or company size of the listed companies in the collected sample data, there may be a problem of inconsistent sample data measurement standards. Therefore, it is necessary to initialize and standardize the data samples to ensure the dimensional consistency of the sample data. If there are data samples with inconsistent dimensions, it may cause poor convergence of the classification model algorithm, resulting in prediction bias. Therefore, it is necessary to standardize the sample data before training and classification prediction. The index attribute reduction in this article is programmed on MATLAB, and the result is obtained by running. In the standardization process, the premnmx function is used for data dimensionless processing, and the standardized data samples will fall in the interval  $[-1, 1]$  [20].

The information entropy of the category is as follows:

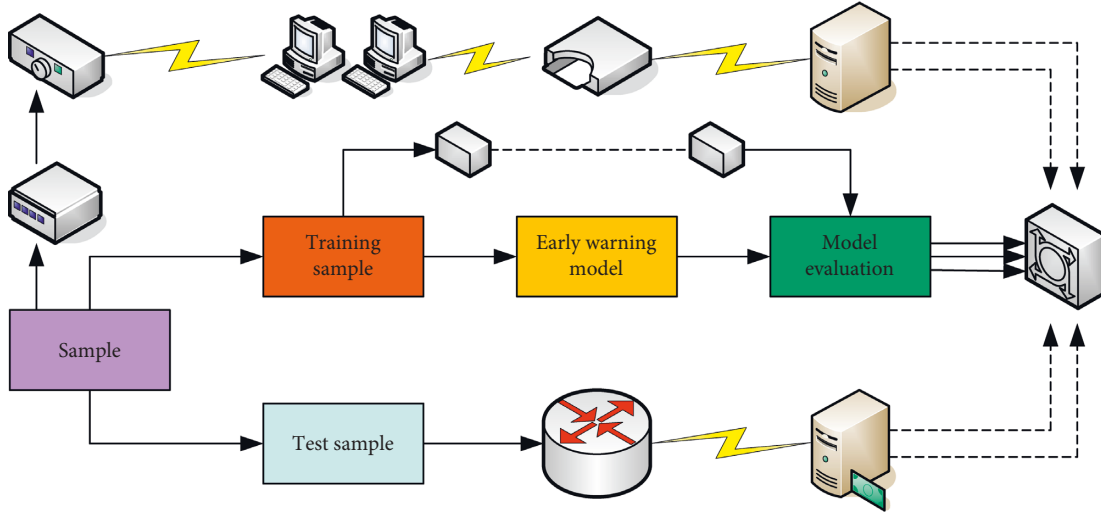


FIGURE 1: Early warning model development and evaluation.

$$\begin{aligned}
 H(C) &= - \sum_{j=1}^k P(C_j) \log_2(P(C_j)) \\
 &= - \sum_{j=1}^k \frac{\text{freq}(C_j, T)}{|T|} \log_2 \left( \frac{\text{freq}(C_j, T)}{|T|} \right).
 \end{aligned} \tag{18}$$

Among them,

$$T = MN_1 + MN_2, \tag{19}$$

where  $MN$  is the standardization coefficient.

The category conditional entropy is as follows:

$$\begin{aligned}
 H(C|V) &= - \sum_{i=1}^n P(v_i) \sum_{j=1}^k P(C_j|v_i) \\
 &= - \sum_{i=1}^n \frac{|T_i|}{|T|} \sum_{j=1}^k \frac{|C_j v_i|}{|T_i|} \log_2 \frac{|C_j v_i|}{|T_i|}.
 \end{aligned} \tag{20}$$

Among them,

$$\begin{aligned}
 H(C) &= \frac{- \sum_{i=1}^n P(v_i) \sum_{j=1}^k P(C)}{v}, \\
 v &= \beta r.
 \end{aligned} \tag{21}$$

where  $v$  is a statistical variable.

**2.2.1. Statistical Analysis.** This article preliminarily determines the index variables that can be used for difference analysis. This paper conducts independent sample  $t$ -tests on various financial indicators of the sample from 2017 to 2020 and selects financial indicators with differences as the preliminary research variables in the research model of this article. On this basis, through the establishment of a Logistic model, the regression analysis of the index variables entering the model and the explained variables of whether the company will be ST is carried out, and the analysis results of this article are obtained.

**2.3. Correlation Analysis of Variables.** The correlation between variables will affect the use of the model, so before building the model, we need to eliminate the influence of these correlations. This article mainly analyzes the correlation between variables and the autocorrelation of the variables themselves. Considering that the impact of macroeconomic variables on corporate finance is related to the duration of macroeconomic variables, this paper chooses a two-year time window. In other words, if SMEs are marked as ST in year T, financial information data, nonfinancial information data, and macro public information data in T-2 years are needed for analysis and modeling. This article mainly conducts a statistical test on the initially selected index system according to the matching principle of the same industry and similar asset scale. In order to obtain continuous variables with different mean values in the overall sample, and noncontinuous variables related to whether the sample enterprises are nonperforming samples, this paper mainly conducts statistical tests on the index system of the primary selection based on the matching principle of the same industry and similar asset scale. The basic process of index inspection is shown in Figure 2.

**2.4. Results of Risk Prediction of Corporate Financial Data.** In the process of using the Logistic model, it is assumed that the probability of a normal business enterprise to continue to survive is 1, and the probability of a business facing bankruptcy to continue to produce is 0. By bringing the data of other companies into the Logistic model, if the probability  $P$  value is higher than 0.5, it means that the company can continue to operate normally. If the probability  $P$  value is lower than 0.5, it means that the enterprise will face the risk of failure and bankruptcy. Logistic model analysis results are shown in Table 1.

M Group was established in 1988 and officially started operating real estate-related businesses in 1993. In 2001, it became the first batch of listed companies after the lifting of the ban. At present, it has become a well-known real estate company that is highly representative and competitive in the

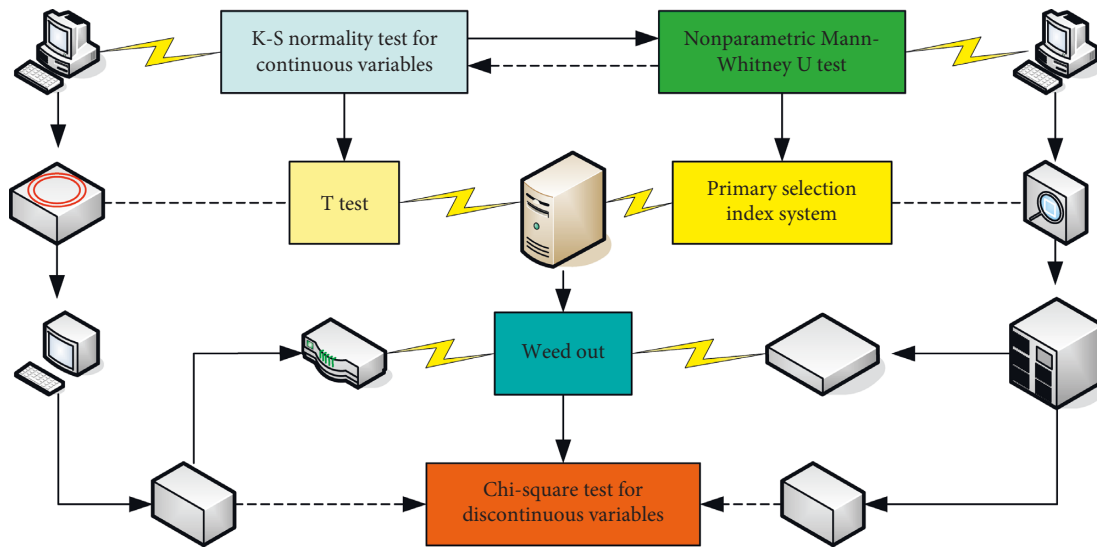


FIGURE 2: The basic process of index verification.

TABLE 1: Logistic model analysis results.

| Logistic model coefficient test |            |          |            |
|---------------------------------|------------|----------|------------|
| —                               | Chi-square | Df value | Sig. value |
| Order                           | 25.357     | 6        | 0.001      |
| Segmented                       | 26.367     | 7        | 0.002      |
| Model                           | 27.393     | 8        | 0.001      |

industry. So far, in addition to residential construction and commercial real estate construction, M Group’s main business has also developed real estate fund investment, tennis clubs, and related real estate services. With the continuous development of various businesses of the enterprise, the popularity and credibility of the enterprise have also been continuously improved. Some of the financial indicators of M Group in the past 4 years are shown in Table 2.

In terms of the basic elements of the degree of stock concentration separation in the listed Internet of Things industry, at the 5% confidence level, the shareholding ratio of the largest shareholder is positively correlated with corporate financial performance. That is, with the increase in the shareholding ratio of the largest shareholder, the financial performance of the enterprise will also be improved, and the result is significant. The Internet of Things industry is combined with the high-risk and high-return characteristics of the technology-intensive industry. Appropriate concentration of equity can reduce the phenomenon of wrangling among shareholders, which is conducive to decision-making in an uncertain environment, thereby promoting the development of the enterprise. The degree of separation of equity checks and balances is positively related to corporate financial performance. That is to say, with the enhancement of the ability of equity checks and balances, the financial performance of enterprises will also improve. However, the result is significant and fails to confirm the previous hypothesis. Although the balance of equity restricts the possible negative effects of “one share dominance,” the

balance of equity is also accompanied by corresponding costs. That is, the divergence and opposition brought about by checks and balances reduce the efficiency of corporate governance. For listed Internet of Things companies, their equity is often concentrated in the hands of a small number of founders, and the negative impact of the “disagreement effect” caused by disagreement will be particularly significant. Figure 3 shows the relationship between the degree of separation of equity checks and balances and corporate financial performance.

However, only by constructing a financial risk model, it analyzes the financial risk status of Group J; it cannot have a comprehensive understanding of the current financial risk status of Group M. After all, the financial risk model is not perfect, and it has no way to reflect all the financial problems faced by M Group’s claims. Therefore, the following will compare the main indicators of the five major financial capabilities of the M Group in 2018 with the standard indicators and combine the current national real estate situation to analyze the current financial problems of the J Group. Table 3 shows the comparison between the main indicators and standard indicators in the five major financial capabilities of M Group.

M company’s capital management relies on an integrated platform, from the preparation of capital plans to real-time control of the capital operation of business activities and investment activities. It achieves the purpose of accelerating capital turnover and reducing capital risks. In recent years, M company, like many domestic counterparts, has suffered a severe shortage of capital flow due to policy factors “barbaric development.” Under this circumstance, Company M established a fund settlement center, adopted a centralized fund management model, and carried out a centralized deployment of cash flow. The control of fund payment has been strengthened to ensure that the full payment is received and the payment is orderly, ensuring that the capital chain is not broken. The optimization of financial management is shown in Table 4.

TABLE 2: Some financial indicators of M Group in the past 4 years.

| Project                                 | 2017     | 2018    | 2019     | 2020      |
|---|----------|---------|----------|-----------|
| Total liabilities (ten thousand yuan)   | 5181191  | 6435831 | 7152451  | 8589191   |
| Total assets (ten thousand yuan)        | 7281 651 | 9151111 | 11252111 | 12392611  |
| Assets and liabilities (%)              | 71.15    | 71.11   | 69.76    | 69.31     |
| Current assets (ten thousand yuan)      | 7187321  | 8823821 | 9814561  | 11 113411 |
| Current liabilities (ten thousand yuan) | 3254931  | 4898131 | 4975371  | 6115251   |
| Current ratio                           | 2.18     | 1.81    | 1.97     | 1.83      |

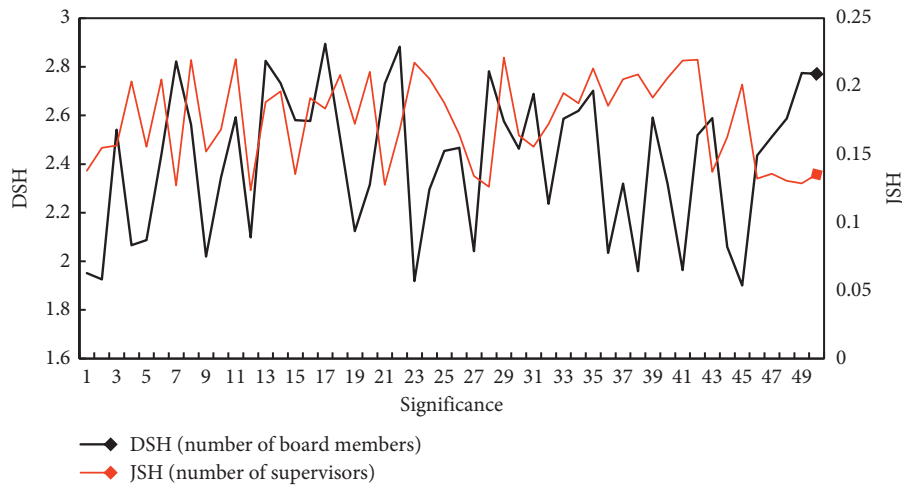


FIGURE 3: The relationship between the degree of separation of equity checks and balances and corporate financial performance.

TABLE 3: Comparison of main indicators and standard indicators in the five major financial capabilities of M Group.

| Project             |  | M Group  | Standard ratio |
|---------------------|--|----------|----------------|
| Solvency            | Current ratio (%)                            | 1.9389   | 2              |
|                     | Quick ratio (%)                              | 0.5504   | 70             |
| Profitability       | Equity ratio (%)                             | 190.8365 | 120            |
|                     | Net sales profit margin (%)                  | 10.8773  | 15.3           |
| Operating capacity  | Roe (%)                                      | 12.7     | 3              |
|                     | Turnover rate of accounts receivable (times) | 2962.7   | 5.6            |
| Development ability | Inventory turnover rate (times)              | 0.4216   | 7.8            |
|                     | Growth rate of total assets (%)              | 0.598    | 0.3            |
| Cash flow           | Sales profit growth rate                     | 10.0619  | 0.5            |

TABLE 4: Optimization of financial management.

| Number | Project                       | Cost budget before optimization of financial management | Cost budget after optimization of financial management |
|--------|-------------------------------|---|--|
| 1      | Repair cost                   | 64.4  | 61.25  |
| 2      | Other fees                    | 214.2   | 206.94   |
| 3      | Other manufacturing expenses  | 78.8  | 74.24  |
| 4      | Other sales expenses          | 74.4  | 72.14  |
| 5      | Other administrative expenses | 52  | 45.44  |

Taking M company’s investment in a certain engineering project as an example, under the premise of not changing its operating income, it reduces various financial losses through effective cost management, asset management, capital

management, and internal control optimization. It handled financial profitability and balance better and increased net profit from RMB 33.653 million to RMB 44,040,700. It has risen by 30.87%, and the investment yield, investment



TABLE 5: Financial management optimization plan improvement.

| Serial number | Financial indicator                        | Budget before optimization | Optimized budget |
|---------------|--|----------------------------|------------------|
| 1             | Internal rate of return (%)                | 21.1%                      | 26.46%           |
| 2             | Return on investment (%)                   | 17.82%                     | 24.42%           |
| 3             | Financial net present value ( $i = 12\%$ ) | 949.96                     | 1449.67          |
| 4             | Payback period (years)                     | 6.16                       | 4.46             |

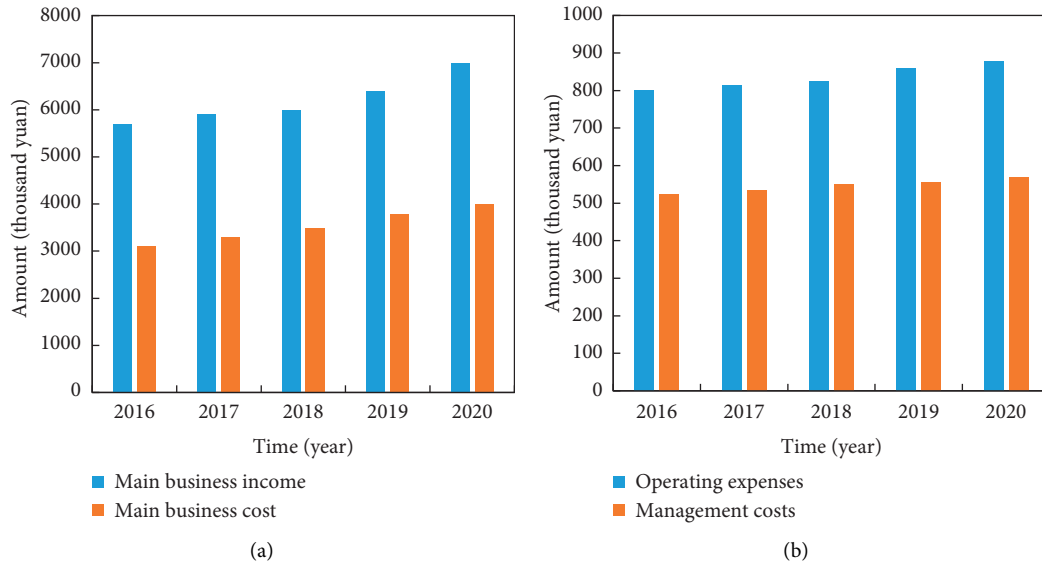


FIGURE 4: Absolute number indicator trend. (a) Main income and expenses. (b) Period expenses and total profits.

payback period, net present value, and internal rate of return have improved to varying degrees. It fully demonstrates that this financial management optimization program can significantly improve the economic benefits of the project. The improvement of the financial management optimization plan is shown in Table 5.

This paper analyzes the indicator trend of indicators related to annual data through the main business income, main business cost, period expenses, total profit, and other elements (Figure 4).

At the significance level of  $\alpha = 0.05$ , only the  $P$  value of the  $K$  statistic, the asset-liability ratio, and the shareholding ratio of the largest shareholder is greater than 0.05 (the net profit growth rate and return on equity are shown in Figure 5(a)). Therefore, only the asset-liability ratio and the shareholding ratio of the largest shareholder conform to the normal distribution, and the samples of the remaining 20 indicators do not conform to the normal distribution (the ratio of net profit cash content to the current ratio is shown in Figure 5(b)).

This paper conducts principal component analysis on the sample (the initial eigenvalues are shown in Figure 6(a)). For the sample data of the nine early warning indicators (asset-liability ratio, return on net assets, financial expense ratio, main business profit ratio, earnings per share, accounts receivable turnover rate, audit opinion, interest protection multiple, and return on total assets) that enter the screening, SPSS software is used to perform principal component analysis (extract the sum of squares and load it as shown in Figure 6(b)).

The regression coefficients and significance test results of the board of directors and the board of supervisors are shown in Table 6. In terms of the basic elements of the structure of the board of directors and the board of supervisors of the listed Internet of Things industry, at the 5% confidence level, the following conclusions are made. The number of board of directors is negatively related to the financial performance of the enterprise; that is, as the number of board of directors increases, the financial performance of the enterprise decreases. However, the result is not significant and fails to confirm the previous hypothesis. It can be seen that although too many shareholders are likely to cause divergence and even opposition, which reduces the efficiency of decision-making, however too few shareholders can also lead to excessive concentration of rights and trigger a series of negative effects. The number of board of supervisors is negatively correlated with the financial performance of the enterprise, which verifies the previous hypothesis. It shows that the board of supervisors system has not played a role in the abuse of checks and balances as expected, thereby improving the financial performance of the enterprise. But the result is not significant. The proportion of independent directors is positively correlated with corporate financial performance. That is, as the proportion of independent directors in the board of directors increases, the financial performance of the company is also improved, and the result is significant, which confirms the previous hypothesis. It can be seen that independent directors have played a good role in promoting the production and

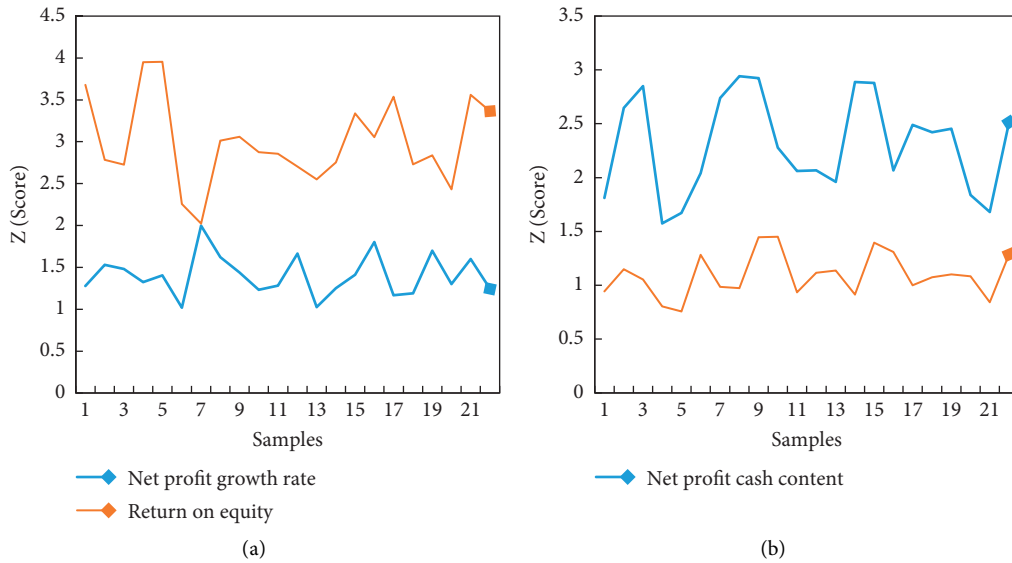


FIGURE 5: Significance level test. (a) Net profit growth rate and return on equity. (b) The ratio of cash content of net profit to the current ratio.

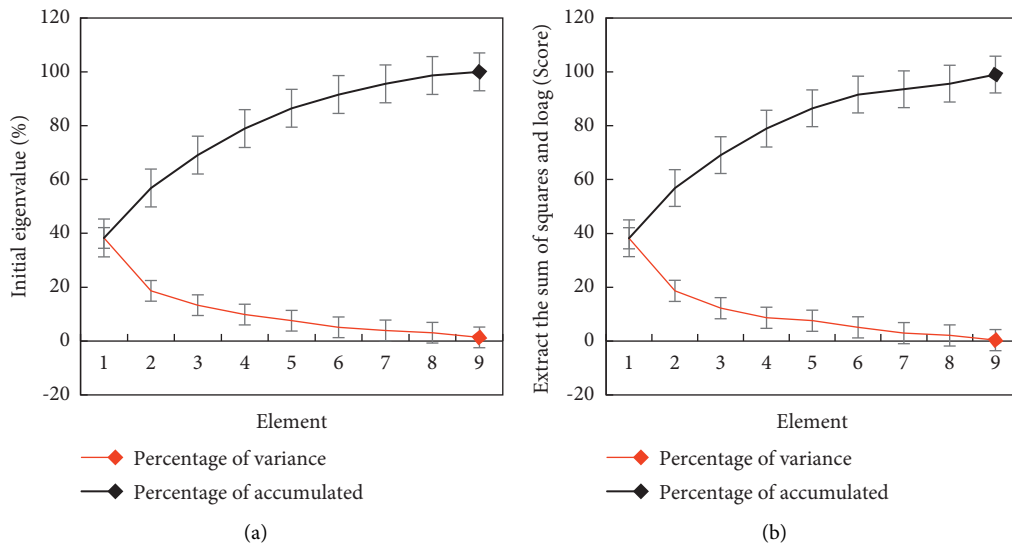


FIGURE 6: Variance interpretation results. (a) Initial characteristic value. (b) Extract the sum of squares and load.

TABLE 6: Regression coefficients and significance test results of the board of directors and the board of supervisors.

| Model parameters                          | Correspondence coefficient | Significance |
|---|----------------------------|--------------|
| DSH (number of board members)             | -0.032856                  | 0.0805       |
| JSH (number of supervisors)               | -0.018201                  | 0.6190       |
| DLD (percentage of independent directors) | 0.009209                   | 0.0112       |

operation of enterprises by virtue of their professional ability and neutral position.

The dominant variable of principal component 1 is return on net assets, and the factor load is 0.955, which is significantly higher than other indicators. Although the factor load of earnings per share is 0.954, it is also very high. But when this article further analyzes the correlation between return on equity and earnings per share, it is found that the correlation coefficient is 0.854, and there is a serious correlation between

the two. This article discards one and retains the return on net assets as the main component of the representative index (return on equity, earnings per share, and profit rate of main business as shown in Figure 7(a)). This article interprets principal component 1 as profitability. Its representative index is return on net assets (interest coverage, audit opinion, and return on total assets as shown in Figure 7(b)).

There are two types of misjudgment by the enterprise financial data forecasting risk model for the sample. Type I

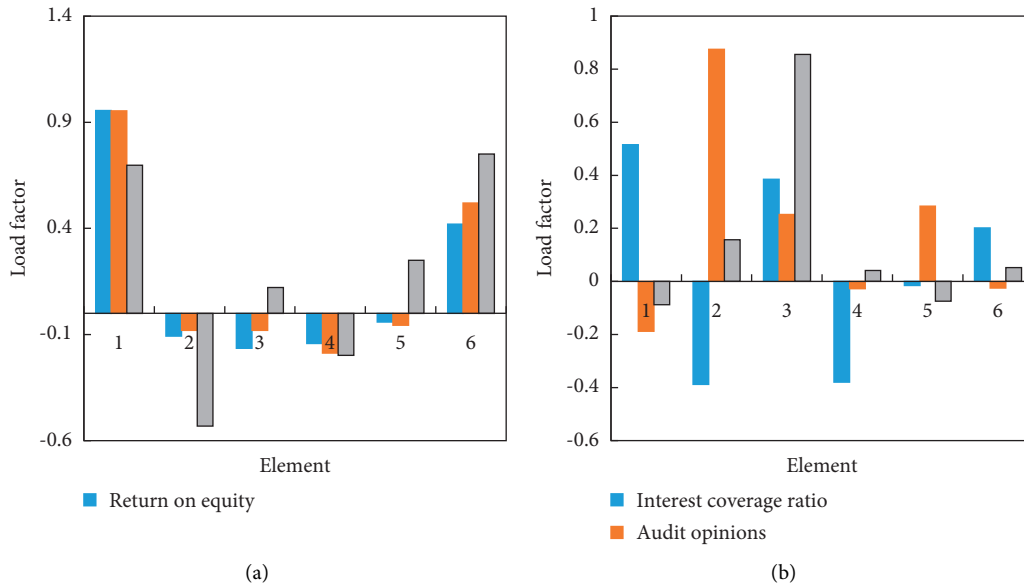


FIGURE 7: Asset returns. (a) Return on equity, earnings per share, and profit margin of main business. (b) Interest coverage ratio, audit opinion, and return on total assets.

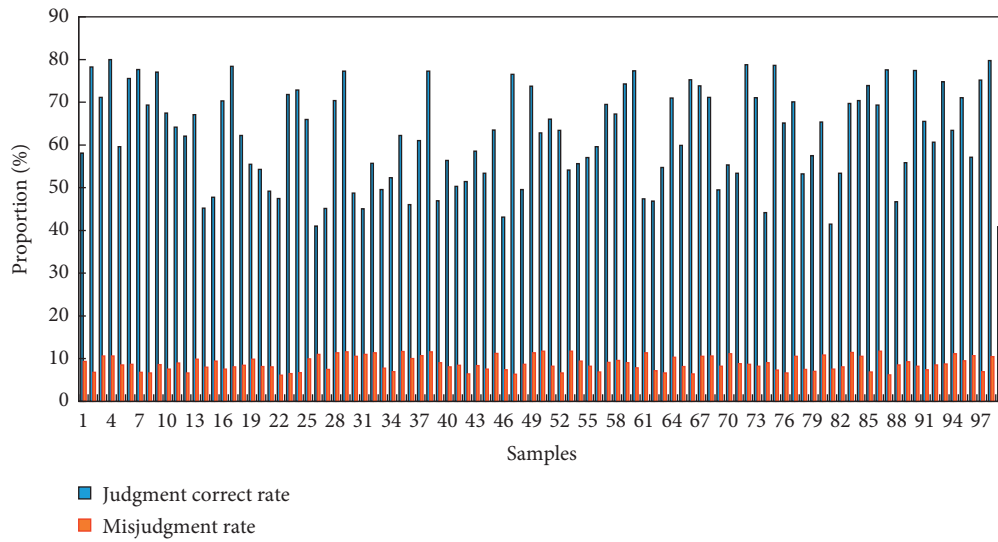


FIGURE 8: Result of false positive rate.

error is to judge a financially distressed enterprise as a financially normal enterprise, and type II error is to judge a financially normal enterprise as a financially distressed enterprise. The experimental results show that, for the training samples, the total number of sample misjudgments is 3. The number of type I and type II errors is 1 and 2, respectively, the misjudgment rate is 2.7%, and the judgment accuracy rate is 97.3%. For the test sample, the number of sample misjudgments is 6, the number of type I and type II errors is 3, the total misjudgment rate is 10.9%, and the judgment accuracy rate reaches 89.1%. In general, the probability of making a type I error is slightly greater than the probability of making a type II error. But the misjudgment rate is below 25%, which is acceptable. The result of the misjudgment rate is shown in Figure 8.

Based on three models, BP neural network model, financial data forecast risk model of this article, and Logistic regression model, this article summarizes the prediction results of 55 test samples, and the results are shown in Figure 9. In the empirical prediction of 55 test samples, the overall discrimination accuracy of the three early warning models is 81.82%, 83.6%, and 89.1%, respectively. Among them, the discrimination accuracy of crisis samples is 66.67%, 58.3%, and 75%, respectively. As a financial early warning model, the overall discrimination accuracy is an important criterion for model selection. At the same time, the discrimination accuracy of crisis samples cannot be ignored. Combining the judgment results of the three methods, the discriminant accuracy of the risk model for predicting corporate financial data in this paper is significantly higher

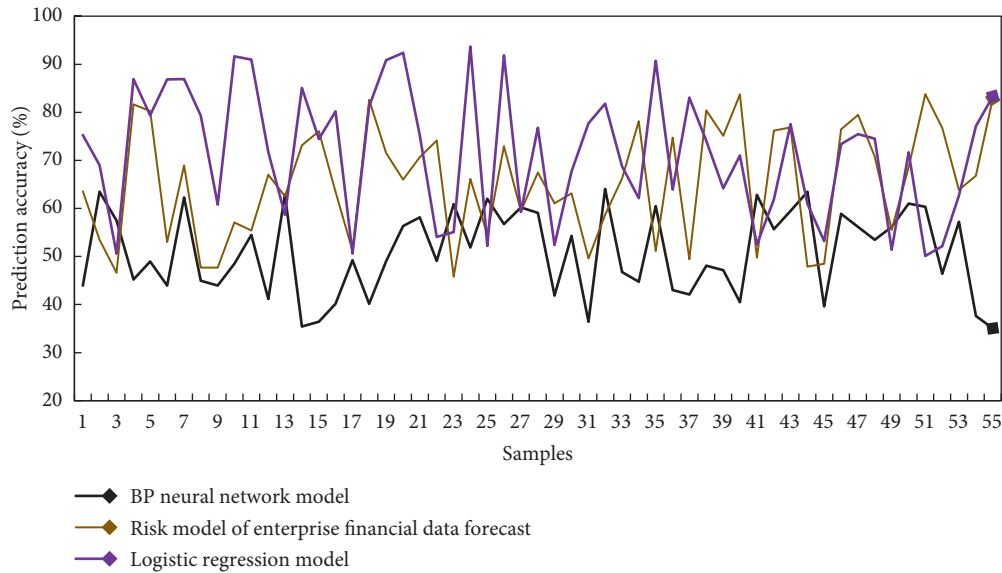


FIGURE 9: Comparison of prediction results.

than the first two. This is due to the strong self-learning ability and fault-tolerant ability of the enterprise financial data forecasting risk model in this paper, which has greater advantages in comparison. Compared with Logistic regression model, the predictive risk model of corporate financial data in this paper is more suitable as an early warning model of corporate financial crisis.

### 3. Discussion

The prospect of the Internet of Things is very attractive, and the social tax revenue and jobs it creates are also very rich. As an emerging industry, a listed company with the concept of Internet of Things, it is considered to be a leader in Internet of Things technology and business opportunities for the Internet of Things. At present, IoT companies are spreading across many fields such as agriculture, manufacturing, communications, and service industries, providing solutions for multiple scenarios such as smart logistics, smart homes, and smart transportation. In the face of an increasingly structured and distributed IoT industry chain, it is particularly important to evaluate the performance level and operating efficiency of listed IoT companies at different levels and in different subdivisions in the future.

The operating performance evaluation process of listed companies includes three main steps: index determination, weight division, and standard evaluation. First, establish the key indicators that affect performance, and then disassemble and distinguish each indicator, and finally, set up a unified evaluation standard. Taking into account the actual development of the Internet of Things companies, advancing with the times, the company's cash flow capabilities, scientific research and innovation capabilities, and management capabilities should also be taken into consideration. Therefore, when selecting indicators, the seven aspects are mainly considered.

At present, there are few financial distress risk evaluation index systems and risk measurement models that specifically target the characteristics of the manufacturing industry. Many banks still use common credit rating or credit scoring methods when approving loan applications for equipment manufacturing enterprises, and they are not clearly distinguished from the risk measurement of other industries. This is likely to lead to inaccurate measurement of risks in the manufacturing industry, which in turn will lead to difficulties in the approval of manufacturing loans, improper grant lines, and unreasonable loan interest rates. Changes in macroeconomic conditions and the state of the company's own operations will trigger changes in the credit quality of corporate loans. However, the future credit situation of a company cannot be accurately reflected only by the linear superposition of "individual factors + macro variables" of these two aspects. The sensitivity of enterprise credit status to changes in macroeconomic conditions will vary due to the heterogeneity of the enterprise itself. With the change of economic operation stage, the heterogeneous influence of enterprises will further change.

The development of information technology and computer and network communication technology has accelerated the pace of human beings entering the information age. The support of technology makes modern information services possible and opens up an information highway for people. Information service penetrates into various fields such as government, scientific research, and society, and it makes us know its vigorous vitality and huge growth space.

The financial risks of listed companies are unavoidable and cannot be eliminated, which is of great significance to the management and control of financial risks. If a listed company does not pay attention to the supervision and control of the financial status, it is very likely that the capital will be broken, causing immeasurable losses to the company. Financial accounting information is an important type of information carrier for the company. Because it has a long

history, strict disclosure system, and uses scientific methods to record the company's financial status and operating results, it has a high use value. Through the mining of high-quality information, users of information can fully understand the company and discover problems in operations in a timely manner. Therefore, it is helpful for company managers to use appropriate and accurate financial risk prediction methods to evaluate the company's financial risk level, which will help to fully understand the company's capital use. Before the company's financial risk reaches a certain level, timely warning messages are issued to managers, so that targeted countermeasures can be taken to prevent things from deteriorating and causing immeasurable losses. For company stakeholders, using appropriate and accurate financial risk prediction methods to evaluate the company's financial risk level will help investors make correct investment decisions. Through the mining of high-quality financial accounting information, it provides decision-making support for investors, creditors, and other stakeholders and improves decision-making efficiency.

Aiming at the particularity of information service companies, referring to the literature on selection of relevant financial forecast indicators, this paper selects indicators that can reflect the characteristics of the information service industry. The characteristics of the industry have an important influence on the development of the company. When company managers predict the company's crisis, they must take into account the specific industry characteristics of the company and take corresponding countermeasures. The addition of two special indicators of company size makes the indicator system more perfect and reasonable. The input samples of the model are therefore more representative, which will greatly improve the prediction accuracy of the model.

#### 4. Conclusion

Combining the relevant theories of corporate governance, through the analysis of the corporate governance structure, financial performance of listed Internet of Things companies, and the relationship between the two, this article attempts to find the elements that play a key role in many corporate governance structure elements. And it clarifies the form of its function. It is hoped that, through the research of this article, the theoretical level can enrich the research results of related fields. On a practical level, it can be beneficial to the healthy development of IoT enterprises and even the IoT industry. In future research, a method will be found to explain the role of unobservable heterogeneity in the financial distress forecasts of listed Chinese manufacturing companies. In order to take into account the unobservable heterogeneity of common factors, this paper estimates a panel data model. The usual fixed or random effects are replaced by multi-factor error structures.

#### Data Availability

The data used to support the findings of this study are available from the author upon request.

#### Conflicts of Interest

The author declares no conflicts of interest.

#### References

- [1] H. Shang, D. Lu, and Q. Zhou, "Early warning of enterprise finance risk of big data mining in internet of things based on fuzzy association rules," *Neural Computing & Applications*, vol. 33, no. 9, pp. 3901–3909, 2021.
- [2] Y. Bogodistov and V. Wohlgemuth, "Enterprise risk management: a capability-based perspective," *The Journal of Risk Finance*, vol. 18, no. 3, pp. 234–251, 2017.
- [3] H. K. Baker, S. Kumar, S. Colombage, and H. P. Singh, "Working capital management practices in India: survey evidence," *Managerial Finance*, vol. 43, no. 3, pp. 331–353, 2017.
- [4] B. Paraque, "The need for an alternative to shareholder value creation? The Ethomed student experience," *Research in International Business and Finance*, vol. 39, pp. 686–695, 2017.
- [5] D. Swagerman, V. J. Steenis, and P. Sieber, "Shared services in accounting and finance," *Organizational Virtualness – Proceedings of the VoNet-Workshop*, vol. 17, no. 6, pp. 63–65, 2017.
- [6] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "An application - specific protocol architecture for," *IEEE Transactions on Wireless Communications*, vol. 1, no. 4, pp. 660–670, 2017.
- [7] Z. L. Wang, "Functional oxide nanobelts: materials, properties and potential applications in nanosystems and biotechnology," *Annual Review of Physical Chemistry*, vol. 55, no. 1, pp. 159–196, 2019.
- [8] D. Helbing, G. Tröster, and M. Wirz, "Recognition of crowd behavior from mobile sensors with pattern analysis and graph clustering methods," *Networks and Heterogeneous Media*, vol. 6, no. 3, pp. 521–544, 2017.
- [9] L. V. Hoesel, T. Nieberg, and W. Jian, "Prolonging the lifetime of wireless sensor networks by cross-layer interaction," *IEEE Wireless Communications*, vol. 11, no. 6, pp. 78–86, 2017.
- [10] Z. P. Pang, E. Melicoff, and D. Padgett, "Synaptotagmin-2 is essential for survival and contributes to Ca<sup>2+</sup> triggering of neurotransmitter release in central and neuromuscular synapses," *Journal of Neuroscience*, vol. 26, no. 52, pp. 13493–13504, 2017.
- [11] M. A. Razzaque, M. Milojevic-Jevric, and A. Palade, "Middleware for internet of things: a survey," *IEEE Internet of Things Journal*, vol. 3, no. 1, pp. 70–95, 2017.
- [12] J. P. Wigner, P. Waldteufel, and A. Chanzy, "Two-dimensional microwave interferometer retrieval capabilities over land surfaces (SMOS mission)," *Remote Sensing of Environment*, vol. 73, no. 3, pp. 270–282, 2017.
- [13] X. Zhao, Z. Gao, Z. Li, and H. Huang, "A highly fluorescent Al<sup>3+</sup>-based metal-organic framework (CYCU-3) for selective and sensitive sensing of 2,4,6-trinitrophenol," *Journal of Porous Materials*, vol. 25, no. 6, pp. 1597–1602, 2018.
- [14] X. Su, P. Shi, and L. Wu, "Reliable filtering with strict dissipativity for T-S fuzzy time-delay systems," *IEEE Transactions on Cybernetics*, vol. 44, no. 12, pp. 2470–2483, 2017.
- [15] W. Olthuis, W. Streekstra, and P. Bergveld, "Theoretical and experimental determination of cell constants of planar-interdigitated electrolyte conductivity sensors," *Sensors and Actuators B: Chemical*, vol. 24, no. 1–3, pp. 252–256, 2017.
- [16] J. Luo, J. Hu, and D. Wu, "Opportunistic routing algorithm for relay node selection in wireless sensor networks," *IEEE*

- Transactions on Industrial Informatics*, vol. 11, no. 1, pp. 112–121, 2017.
- [17] I. Khan, F. Belqasmi, and R. Glitho, “Wireless sensor network virtualization: a survey,” *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 553–576, 2017.
  - [18] A. W. Nolin, “Recent advances in remote sensing of seasonal snow,” *Journal of Glaciology*, vol. 56, no. 200, pp. 1141–1150, 2017.
  - [19] A. Liu, G. Liao, and Z. Cao, “An eigenstructure method for estimating DOA and sensor gain-phase errors,” *Digital Signal Processing*, vol. 59, no. 12, pp. 5944–5956, 2018.
  - [20] K. Birch, “Rethinking value in the bio-economy,” *Science, Technology & Human Values*, vol. 42, no. 3, pp. 460–490, 2017.