Research Article

Construction of Enterprise Financial Early Warning Model Based on Intelligent Mathematical Model

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In order to improve the ability of enterprises to cope with financial risks, this paper analyzes the financial early warning of enterprises combined with intelligent mathematical models and builds an intelligent financial early warning model to assist in analyzing the financial status of enterprises. Moreover, this paper combines the existing information technology and expenditure business scenarios to construct an intelligent early warning frame for enterprise financial control based on an intelligent mathematical model. In addition, this paper combines the K-means clustering algorithm to design a financial approval process integrity control early warning method to warn the integrity of the financial approval process. Finally, this paper presents the early warning of financial standard compliance control based on the C4.5 decision tree algorithm. The experimental research shows that the enterprise financial early warning model based on the intelligent mathematical model proposed in this paper can play an important role in the enterprise financial management and effectively improve the ability of the enterprise to cope with financial risks.

1. Introduction

Financial risk corresponds to business risk in a relatively narrow sense. It refers to a risk situation in which investors’ expected returns are reduced due to unreasonable corporate financial status and improper financing, and, at the same time, the company may lose its solvency. The financial early warning system we discuss and build here does not only refer to the company’s financial debt crisis but is a financial concentrated manifestation of various internal contradictions and external risks that exist and are latent in the company’s operation process.

The generation of financial risks is the result of internal and external contradictions, and these changes in financial early warning and its unfavorable influencing factors are called “warning sources.” “Alert source” is divided into endogenous “alarm source” and exogenous “alarm source.” To a certain extent, the endogenous alarm source is controllable, because this kind of problem is not directly related to the production management of the company, while the exogenous alarm source is on the contrary; this kind of problem is beyond the control of the company, so it is more harmful. It is manifested as the uncertainty of the political environment, the uncertainty of the natural environment, the uncertainty of the industry competition environment, and the uncertainty of the economic environment. Because the company’s operation is to pursue the maximization of profits, but high returns are often accompanied by high risks, and financial risks are everywhere in the company’s production and operation process, if it is allowed to continue to develop beyond the company’s risk tolerance, then there will be financial crises such as bankruptcy. Financial risks are not out of control from the beginning. According to medical terms, they can be divided into incubation period, development period, and deterioration period. Each stage has a relatively obvious and unique appearance, which is called “warning sign.” Therefore, if you want to effectively prevent and control financial risks, you must pay close attention to
the warning signs in the company’s operation, management, and finance. The company’s goal is to maximize profits, but profits and risks are always in direct proportion to each other, and the normal operation of the company will face various crises. Therefore, with the emergence of warning signs at different stages, the company also needs to take various effective measures in a timely manner to prevent the further development and deterioration of the warning situation. In the early stage, warning signs are usually single, with only a little hidden change in one aspect of financial indicators, and it is usually difficult to attract the attention of the company’s top management at this stage. The production and operation and financial status of the company have been greatly impacted, and the financial risk has further deteriorated; in the end, the crisis is severe, and the company can only face bankruptcy.

This paper combines the intelligent mathematical model to analyze the financial early warning of the enterprise and constructs an intelligent financial early warning model to assist in the analysis of the financial situation of the enterprise and improve the ability of the enterprise to deal with the financial crisis.

2. Related Work

Literature [1] believes that the poor effect of enterprise risk management is due to the lack of strong risk awareness of executives, and there is no appropriate method to manage enterprise risk. After the emergence of the term risk management, the related theories have officially become popular in academia. Literature [2] further defines risk management as the use of economic or technical means to reduce enterprise risks to the lowest level under the premise of analyzing the risk factors existing in each business link. In this definition, the purpose of enterprise risk management is clearly stated, that is, to reduce enterprise risk. With the popularity of risk management, scholars have gradually linked risk management with corporate financial activities, and the importance of financial risk management has been paid attention to. Literature [3] puts forward the theory of enterprise adversity management, expounds the causes and laws of business failure, management fluctuation, management behavior mistakes, and other phenomena, and conducts theoretical analysis on how to prevent and deal with enterprise adversity. Based on the theory of enterprise adversity management, literature [4] proposes an early warning and precontrol management model to deal with the adverse effects of business failure or management errors. The early warning and precontrol management model provides a literature for the theoretical study of financial risk early warning. Literature [5] believes that financial risk early warning is not only the identification of enterprises with high financial risks but also the early warning of enterprises whose financial risks may increase. Literature [6] believes that financial risk early warning is a process of using the risk early warning value and the actual value to measure the financial risk level of the enterprise and return the early warning results based on the financial status of the enterprise and the internal and external environment.

As an important way of financial risk management, financial risk early warning has received attention, and there have been a large number of studies on early warning indicators, and some scholars have integrated cross-disciplinary research methods into financial risk early warning models, further enriching the types of models. Literature [7] uses a single financial indicator to predict financial risk and designs a univariate early warning model. Literature [8] uses the financial data of 79 companies to compare and analyze two types of companies that fail to operate and operate normally based on 30 financial ratios. It is found that the most accurate prediction is the debt coverage ratio indicator, followed by the asset-liability ratio indicator, and prediction success rates improve as bankruptcy day approaches. This study still does not use indicators with higher prediction accuracy to construct an early warning model that can be used for a long time but analyzes the relationship between the prediction accuracy of indicators and the time of financial crisis outbreak. Literature [9] studies off-balance sheet indicators, and the results show that company size, capital structure, and asset realization ability can make financial risks change significantly. This study shows that nonfinancial indicators with a high degree of correlation with corporate financial risks can be considered when selecting early warning indicators. Literature [10] uses the catastrophe theory to carry out financial risk early warning and proves that it has certain applicability. Literature [11] uses the BCC model of data envelopment analysis for index analysis and risk prediction and compares it with the Z-score model, which proves that the data envelopment analysis method is suitable for financial risk early warning and has higher accuracy. Literature [12] divides the deterioration process of enterprise risk into latent, onset, and deterioration periods and explores the omens of financial risks from the perspectives of internal control and external environment and proposes that enterprises should set up an alert monitoring system. The discussion of warning signs in this study provides ideas for the selection of early warning indicators, emphasizing the impact of external factors on corporate financial risks. Literature [13] conducts text sentiment analysis on the information related to listed companies on the Internet through web crawler, forms sentiment indicators, and constructs a financial risk early warning model incorporating sentiment indicators. This study takes sentiment indicators into consideration and provides ideas for indicator selection from different perspectives. Literature [14] proposes using partial least squares method to screen early warning indicators, which proves that this method can effectively improve the accuracy of model prediction, and provides a new indicator screening method. Literature [15] quantifies the emotional description in management discussion and analysis to form sentiment index and finds that the model that introduces this sentiment index has a higher classification accuracy, which proves that some effective information in the management discussion and analysis can predict the future performance level of the enterprise to a certain extent. This study takes into account the effect of management discussion and analysis on early warning, which enriches the perspective of indicator selection.
Literature [16] draws the conclusion that property rights ratio and equity net interest rate are two financial indicators with strong early warning ability. Using the single financial indicators of 19 companies to analyze, research on enterprise financial risk early warning is conducted. The early warning research at this time is based on the direct corresponding relationship between a single indicator and the financial risk of the enterprise, and the relationship of each indicator is relatively independent. Literature [17] is one of the intelligent models of univariate financial risk early warning model established by using 30 financial indicators. Literature [18] uses statistical methods to build a financial risk early warning model. Literature [19] researches and analyzes 66 companies from the perspectives of profitability, solvency, and current ratio, establishes a Z-score model, uses financial companies from the perspectives of profitability, solvency, and current ratio, establishes a Z-score model, uses financial warning indicators and combines statistical methods, and uses multivariate linear discrimination in financial risk early warning method. The model uses multiple variables for analysis, which overcomes the shortcomings of the single-variable model to a certain extent and is more comprehensive.

3. Enterprise Financial Early Warning Process Based on Intelligent Mathematical Model

The integrity control of the approval process is reflected in the three levels of control over the unit business, relevant departments and positions, and approval efficiency and approval quality. On the basis of constructing the pre-warning indicators for the integrity of the administrative expenditure approval process under the financial cloud platform, after sorting out the corresponding indicator data, scientific methods are needed to classify the data reasonably, to decide the target process that requires early warning, and to achieve the division of early warning levels.

K-means algorithm is a classic, simple, and fast clustering algorithm and is often used in evaluation analysis. According to the designed warning level, the sample data is given for training and learning, so as to achieve a reasonable classification of the sample data. The classification of enterprise expenditure approval process integrity warning needs to be given training data for unsupervised learning. After that, the early warning indicators of various types of data are analyzed and clustered, and the early warning levels are divided.

In the early warning of the integrity of the enterprise expenditure approval process, it is not necessary to know the warning level of each sample data in advance but only the number of categories that the data is finally divided into. In this chapter, the early warning is set to four levels, namely, level 1 early warning, level 2 early warning, level 3 early warning, and complete, that is, \( K = 4 \). The idea of K-means clustering is roughly to randomly select K data from the sample as the initial “cluster center.” It then calculates the distances of the remaining samples to the “cluster centers,” assigns them to the closest clusters, and finally recalculates the “cluster centers” for each cluster. The algorithm itself has the function of optimization and iteration. It iteratively corrects and prunes the existing clusters to determine the clustering of the samples and finally classifies all the sample data according to the similarity, which overcomes the uncertainty of the clustering of a small number of samples.

The samples are \( x^{(i)} = \{x_{i1}^{(i)}, x_{i2}^{(i)}, \ldots, x_{ip}^{(i)}\} \) and \( x^{(j)} = \{x_{j1}^{(j)}, x_{j2}^{(j)}, \ldots, x_{jp}^{(j)}\} \), where \( i, j = 1, 2, \ldots, m \) represents the number of samples and \( n \) represents the number of features. There are three main methods for calculating the distance from the sample to the “cluster center.”

### 3.1. The Ordered Attribute Distance Is Used to Measure the Minkowski Distance.

\[
dist_{mk}(x^{(i)}, x^{(j)}) = \left( \sum_{u=1}^{n} \left| x_{u}^{(i)} - x_{u}^{(j)} \right|^p \right)^{1/p}. \tag{1}
\]

Euclidean distance is the Minkowski distance at \( p = 2 \):

\[
dist_{ed}(x^{(i)}, x^{(j)}) = \left( \sum_{u=1}^{n} \left( x_{u}^{(i)} - x_{u}^{(j)} \right)^2 \right)^{1/2}. \tag{2}
\]

Manhattan distance is the Minkowski distance at \( p = 1 \):

\[
dist_{man}(x^{(i)}, x^{(j)}) = \left( \sum_{u=1}^{n} \left| x_{u}^{(i)} - x_{u}^{(j)} \right| \right)^{1}. \tag{3}
\]

Most of the datasets in this paper are continuous attributes, so the Euclidean distance is used for calculation in the algorithm.

### 3.2. Disordered Attribute Distance Metric VDM (Value Difference Metric).

\[
VDM_{p}(x_{u}^{(i)}, x_{u}^{(j)}) = \sum_{z=1}^{k} \frac{\left| m_{u,(v,z)}^{(i)} - m_{u,(v,z)}^{(j)} \right|}{v_{z} \cdot \text{ldyftolri}}. \tag{4}
\]

In the above formula, \( m_{u,(v,z)}^{(i)} \) represents the number of samples whose value is \( x_{u}^{(i)} \) on attribute \( u \), and \( m_{u,(v,z)}^{(j)} \) represents the number of samples whose value is \( x_{u}^{(j)} \) on attribute \( u \) in the \( z \)-th sample cluster. \( VDM_{p}(x_{u}^{(i)} - x_{u}^{(j)}) \) represents the VDM distance between two discrete values \( x_{u}^{(i)} \) and \( x_{u}^{(j)} \) on attribute \( u \).

### 3.3. The Mixed Attribute Distance Measure Is the Combination of Order and Disorder.

\[
\text{MinkovDM}_{p}(x^{(i)}, x^{(j)}) = \left( \sum_{u=1}^{n} \left| x_{u}^{(i)} - x_{u}^{(j)} \right|^p \right)^{1/p} + \sum_{u=n+1}^{n} VDM_{p}(x_{u}^{(i)}, x_{u}^{(j)})^{1/p}. \tag{5}
\]

It contains \( n_c \) ordered attributes and \( n - n_c \) unordered attributes.

Based on the steps of the K-means clustering algorithm, this paper combines the characteristics of the enterprise expenditure approval process integrity control early warning process to construct the expenditure approval process integrity control early warning process, as shown in Figure 1.
After extracting the early warning indicators of the integrity control of the enterprise expenditure approval process, it is necessary to collect data according to the characteristics of the samples. In order to fully reflect the integrity control of the enterprise expenditure approval process, the coverage of the approval process, the efficiency of the approval process, and the quality of the approval process are included in the scope of the sample characteristics. In order to meet the needs of early warning data for the integrity control of the expenditure approval process, it is necessary to collect portal information, fund approval, financial accounting, payment inquiry, expense reimbursement, expenditure economic classification, and other module data related to expenditure approval records, process settings, expenditure business classification, and expenditure audit post information from the expenditure management database of the unit’s financial cloud platform.

The basic principle of the K-means clustering algorithm is to set the clustering parameter K, randomly select K data samples as the “cluster center,” and then calculate the distance between the remaining sample data and each “cluster center” by the Euclidean formula. Finally, it assigns all the data to the nearest cluster to achieve classification. At the same time, the algorithm will iteratively correct and prune the clustering of the data samples on the basis of the existing clustering and optimize the unreasonable parts of the initial unsupervised learning sample classification. The specific process is shown in Figure 2.

3.3.1. The Algorithm Defines the Sample Dataset X. The approval process integrity control early warning dataset after cleaning and conversion is defined as sample $x^{(i)} = \{x_1^{(i)}, x_2^{(i)}, \ldots, x_n^{(i)}\}$, where $i = 1, 2, \ldots, m$ represents the number of samples and $n$ represents the number of features.

3.3.2. The Algorithm Sets the Clustering Parameter K. The first step for K-means to implement clustering is to set the clustering parameters. Since this chapter divides the expenditure approval process integrity control early warning into four levels, process integrity, level 3 early warning, level 2 early warning, and level 1 early warning, the clustering parameter $K = 4$ is set.

3.3.3. The Algorithm Specifies the “Cluster Center”. The number of clusters is 4, so 4 “cluster centers” need to be specified. There are two ways to select “cluster centers”: random method and longest distance method. Among them, the longest distance method is to randomly designate a sample in the sample dataset as the first “cluster center.” Then, the algorithm calculates the distance between the remaining samples and the sample, selects the sample with the farthest distance as the second “cluster center,” and so on, until four “cluster centers” are selected, and the “cluster center” is set to C; that is,
Gain cluster. The calculation formula is as follows:

\[ \text{Gain}(D, C_i) = \max_{x \in T_{c_i}} \text{Gain}(D, C_i, t) = \max_{x \in T_{c_i}} \text{Info}(D) - \sum_{x \in [a, r]} \frac{|D_i|}{|D|} \text{Info}(D_i) \]

The data feature information gain calculation formula for discrete values is the same as above.

After discretizing the features with continuous values, the information entropy of all nodes needs to be calculated. In the training set \( D \), the information entropy calculation formula of feature \( a \) is as follows:

\[ \text{Split Info}_a(D) = -\sum_{j=1}^{n} \frac{|D_j|}{|D|} \log_2 \frac{|D_j|}{|D|} \]

In the above formula, \( n \) is the number of values of feature \( C_i \), which can be expressed as \([C_{i,1}, C_{i,2}, \ldots C_{i,n}]\), and \( D_j \) is the set of sample data in the dataset \( D \) where the value of feature \( C_i \) is \( C_{i,j} \).

The information gain rate is defined. The information gain rate formula can be obtained as follows:

\[ \text{Gain Ratio}(D, a) = \frac{\text{Gain}(D, a)}{\text{Split Info}_a(D)} \]

The information gain rates of all nodes are compared, and the node with the largest information gain rate will
become the root node to divide the data feature. Then, based on the left and right branches of the root node, the information gain rate is calculated for the remaining data features, and the node with the largest gain rate is selected as the next classification node, thus recursing until all the datasets are classified.

Based on the steps of the C4.5 decision tree algorithm, combined with the formulation basis of the enterprise expenditure standard and the characteristics of the data, an early warning process for the compliance control of the expenditure standard is constructed, as shown in Figure 3.

This paper extracts various types of expenditure data from the financial cloud platform of the unit, such as travel expense schedule, conference fee schedule, and training fee schedule. Moreover, this paper uses SQL statements to process the extracted detailed data of various expenditures and removes duplicates, missing values, and other data that will affect the classification results. At the same time, this article deletes irrelevant fields, such as bank account number, entry time, reviewer, and other related fields.

Discrete features such as expenditure category, expenditure details, personnel rank/activity category, and other data feature values cannot be recognized by the algorithm and need to be converted in advance and replaced with ordered numbers like 1, 2, 3, and so on. For standard compliance as the target attribute, 1 means compliance and 0 means noncompliance.

After the defined training sample set is connected to the C4.5 algorithm, the algorithm first discretizes the continuous data features in the expenditure data and realizes the continuous feature discretization by calculating the optimal splitting point. The algorithm then calculates the information gain rate of each feature, selects the classification node by the information gain rate, and generates a decision tree iteratively. At the same time, the algorithm generates various types of expenditure standards to follow the classification rules for situation prediction. The specific process is shown in Figure 4.

The trained C4.5 decision tree algorithm can predict the compliance with the expenditure standard of the actual expenditure data of the unit. The early warning system will issue early warning signals for data that do not meet the expenditure standards and remind financial personnel to check the relevant expenditure details, thereby strengthening the compliance control of corporate expenditure standards.

On the basis of constructing early warning indicators for rationality control of enterprise expenditures, after sorting out the data of each early warning indicator, it is necessary to use scientific methods to classify the rationality control data of expenditures and divide the early warning levels.

Self-organizing feature map network, also known as Kohonen network, is an unsupervised, competitive learning clustering algorithm. Kohonen uses feature mapping to achieve dimensionality reduction of data and reduces high-dimensional data to low-dimensional space for display through geometric relationships. Compared with the non-neural network clustering algorithm, Kohonen has better robustness, high efficiency, and good clustering effect. The Kohonen neural network is used to perform unsupervised clustering on the data of the rationality control of basic expenditures of various institutions and secondary units within the enterprise. According to the clustering results, the data characteristics of each cluster are analyzed, the warning
The levels are divided, and the warning labels are marked on the clustering results. The Kohonen algorithm's steps are summarized as follows:

1. The algorithm initializes the network, neighborhood radius $r_0$, learning rate $lr$, and other parameters and randomly initializes the connection weight $w_{ij} (i = $
1, 2, . . . , n; j = 1, 2, . . . , m) between the input layer node and the competition layer node.

(2) The algorithm inputs training samples and assumes that the input data is an n-dimensional vector, $X = (x_1, x_2, \ldots, x_n)$ has m output nodes, and the total competition layer is g. The algorithm uses the Euclidean distance calculation method to calculate the distance $d_j$ from the sample to each output node and selects the node corresponding to the minimum distance as the winning node $v$. The distance calculation formula is

$$d_j = \left| X - W_j \right| = \left( \sum_{i=1}^{n} (x_i - w_{ij})^2 \right), \quad (i = 1, 2, \ldots, m; j = 1, 2, \ldots, m).$$

(13)

Through steps (1) and (2), the winning neuron can be obtained, that is, the central position of the topological field in the competition layer.

(3) The algorithm determines the neighborhood of neuron V:

$$N_j = \{j \mid \text{find} \{\text{norm} (\text{pos}_j, \text{pos}_v) < r \} \}: \quad j = 1, 2, \ldots, m.$$  \hfill (14)

In the above formula, pos$_j$, pos$_v$ are the locations of neurons $V$ and $j$, respectively, and $r$ is the neighborhood radius. The ownership values in the neighborhood are corrected according to the obtained neighborhood.

(4) The algorithm modifies the weights according to the weight learning rules, and the change of the weights is

$$d_w = lr^r a 2^r (x - w).$$  \hfill (15)

In the above formula, lr represents the learning rate, and function $a 2$ is determined by the neuron spacing $d$, the output $a$, and the learning neighborhood size $r$:

$$a 2(i, q) = \begin{cases} 1, & a(i, q) = 1 \\ 0.5, & a(j, q) = 1 \text{ And } D(i, j) \leq r \\ 0, & \text{ other} \end{cases}$$  \hfill (16)

(5) The algorithm performs reinput and repeats steps (2), (3), and (4) until the end of training.

On the basis of raw data training, experience can be accumulated, so as to realize the rapid classification of expenditure rationality control data. After the clustering is completed, the data characteristics of the clustering results are analyzed and the warning level is calibrated.

After the clustering is completed, it is necessary to identify and train the calibrated expenditure rationality control data and finally realize the early warning of basic expenditure rationality control. SVM, also known as Support Vector Machine, is a supervised learning algorithm commonly used for linear regression and classification. Moreover, the SVM algorithm uses the kernel function to realize high-dimensional space mapping and maximizes the interval between the sample and the decision surface, and the classification idea is simple and effective. In addition, the SVM algorithm has strong generalization ability and can be trained and learned based on a small amount of data. The steps to implement the SVM algorithm are as follows:

(1) The algorithm inputs training samples:

$$X = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}.$$  \hfill (17)

In the above formula, $x_i$ represents the training sample point, $y_i$ represents the category of the sample, and $i = 1, 2, \ldots, n$, $n$ is the number of samples in the training set.

(2) The algorithm selects the applicable kernel function and parameters.

(3) The algorithm constructs the convex quadratic programming problem and solves it.

$$s.t. \sum_{i=1}^{n} y_i a_i = 0.$$  \hfill (18)

In the above formula, $0 \leq a_i \leq C, i = 1, 2, \ldots, n$, and the final solution is $a^* = (a_1^*, a_2^*, \ldots, a_n^*)^T$.

(4) The algorithm calculates $b^*$, where $a_i^*$ is the component of $a^*$ in interval $(0, C)$.

(5) Decision function is constructed:

$$f(x) = \text{sgn}(g(x)), \quad g(x) = \sum_{i=1}^{n} y_i a_i^* k(x_i, x) + b^*$$  \hfill (19)

and, on the basis of verifying the sample data, the algorithm judges the category of $x$ by the value of $f(x)$.

(6) The algorithm judges whether the classification error meets the expectation. If it is satisfied, then the algorithm outputs the result and the algorithm ends. However, if it is not satisfied, the algorithm returns to step (2) to repeat the above process.

Based on the characteristics of enterprise basic expenditure rationality control early warning data, the expenditure rationality control early warning process based on Kohonen-SVM combined classifier is shown in Figure 5.

Through the analysis of the rational control of the basic expenditure of the enterprise, this paper sorts out eight early warning indicators: the size of the unit’s jurisdiction, the number of employees in the unit, the type of expenditure, the amount of expenditure, the proportion of expenditure in the same period, the historical growth rate in the same period, the expenditure per capita, and the rate of incomplete/excess expenditure. After that, this paper assigns the early warning indicators and normalizes them. The
eigenvalues of early warning indicators such as the size of the unit’s jurisdiction, the number of employees in the unit, and the amount of expenditure are processed as decimals between (0, 1). The processing formula is

\[ x_i = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  

(20)

4. **Intelligent Enterprise Financial Early Warning Model**

The financial crisis of a company generally goes through three stages: the latent stage, the development stage, and the deterioration stage. The purpose of constructing financial early warning is to remind the company that it should take
corresponding measures to prevent it before the company has a crisis. The process of the company’s financial crisis is as follows: the warning source causes the warning situation, the warning situation evolves and deteriorates, and the warning signs appear. Therefore, the financial early warning system constructed in this paper will reverse the mentioned process. Its internal principle is shown in Figure 6.

In order to assess whether a company has the ability to adapt to the changing economic environment and seize good investment opportunities, early warning on affordability meets this requirement. Affordability refers to the degree of matching between the cash generated by the various activities of the enterprise and the cash required by the enterprise. If the enterprise’s ability to pay is stronger, that is, the cash generated by the enterprise can meet its own needs, it does not need to borrow money from banks or take other ways to raise funds. When a good investment opportunity arises, the company has enough cash to seize the opportunity and gain income. On the contrary, when an enterprise needs cash, it can only raise funds from the outside, which is called weak ability to pay. If this is the case for a long time, the enterprise will face a large amount of debt, and the pressure to repay the debt will gradually increase, which will ultimately affect the viability of the enterprise. The financial early warning indicator system based on cash flow is shown in Figure 7.

This paper uses the enterprise financial early warning model based on the intelligent mathematical model for simulation research and evaluates the financial data processing and financial early warning effect of the model in this paper, and the results shown in Table 1 and 2 are obtained, respectively.

From the above research, it can be seen that the enterprise financial early warning model based on the intelligent mathematical model proposed in this paper can play an important role in the financial management of enterprises and effectively improve the ability to cope with financial risks of enterprises.
Table 1: Data processing effect of enterprise financial early warning model based on intelligent mathematical model.

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Table 2: Financial early warning effect of enterprise financial early warning model based on intelligent mathematical model.

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5. Conclusion

If an enterprise has a financial crisis, it will not only cause serious economic and reputation losses to the enterprise itself but also cause more serious harm to investors, creditors, and shareholders. Moreover, it leads to losses in industries related to the benefit chain and even negatively affects the entire industry in which the stock is located. In the face of such a huge securities market, how to effectively control these listed companies and maintain the normal operation of the market has become an arduous and important task. At present, most listed companies are mainly manifested by poor cash flow liquidity, unreasonable capital structure, flooding of related-party transactions in the industry, and ineffective company management systems. This paper analyzes the enterprise financial early warning combined with the intelligent mathematical model and constructs an intelligent financial early warning model. The experimental research results show that the enterprise financial early warning model based on the intelligent mathematical model proposed in this paper can play an important role in the enterprise financial management and effectively improve the ability of the enterprise to cope with financial risks.

Data Availability

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

Conflicts of Interest

The authors declare no conflicts of interest.

References


