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APPLICATION OF BP NEURAL NETWORK MODEL IN SUPPLY CHAIN FINANCIAL RISK CONTROL

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Abstract. *The diversification of the market development model has rapidly promoted financial innovation, and the improvement of the supply chain has also given rise to the supply chain financial form. However, the risk problem also arises. In order to effectively control supply chain financial risk and improve the ability of supply chain enterprises to resist financial crises, the application of the BP neural network model in supply chain financial risk control is studied. The BP neural network model is designed to categorize the dynamic risk types of supply chain finance according to the dynamic development characteristics of supply chain finance in the past, with the corresponding weight distribution allocated to each category. The BP neural network model is employed to extract the financial risk characteristics of the supply chain, and a dynamic measurement of supply chain finance is conducted based on the risk characteristics. This paper constructs a supply chain financial risk management model based on the BP neural network model and controls the supply chain financial risk. The experimental results demonstrate that after employing various control methods, the risk exhibits a declining trend, effectively mitigating the financial risk of the supply chain with high efficacy.*
Keywords: BP neural network model, Supply chain, Financial risk, Risk control

1. **Introduction.** The problem of financing difficulties of SMEs has been attached to great importance by all countries, and relevant policies have been introduced to solve their financing problems. As one of the ideas [1,2], supply chain finance, combined with the integration and development of "Internet plus", big data and other technologies, as well as BP neural network model, has gradually attracted the attention of various economic entities in society and has been constantly applied. We should actively and steadily develop supply chain finance, promote supply chain finance to serve the real economy, standardize the development of supply chain finance, and make standardizing the development of supply chain finance a key task for pilot enterprises, and continue to promote supply chain finance practice [3]. With broad application prospects and the guidance and promotion of various policies, commercial banks have begun to settle in gradually, and continue to develop relevant supply chain financial products to improve the service scope and service level of banks [4,5]. Supply chain finance has been developing in China for several years, but there are also many inevitable problems. Different from traditional bank credit business, supply chain finance business is characterized by a large

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number of participants, complex business processes, high degree of specialization, and complex operation links. There are problems such as information asymmetry, falsification of warehouse receipt vouchers, and tampering, which easily lead to a series of moral, credit, and operational risks. Therefore, it is of great significance for supply chain financial risk control.

Scholars have conducted numerous studies on this topic. [6] is based on the fuzzy analytic hierarchy process for analyzing financial risks in enterprise supply chains. Qualitative and quantitative risk control methods are combined to control financial risks, and a financial risk control system is designed by constructing a fuzzy judgment matrix. A comprehensive judgment is proposed for financial risk control methods. However, for large supply chain networks, the use of fuzzy analytic hierarchy process increases the overall complexity and time consumption of the algorithm. [7] proposes to explore the factors that affect the application of supply chain finance in supply chain effectiveness. Explore the four key factors that affect the adoption of supply chain financing, which in turn affects the supply chain effectiveness of Chinese manufacturing enterprises. Furthermore, how supply chain risk mediates the correlation between supply chain financing adoption and supply chain effectiveness. However, in this method, the correlation between supply chain finance and supply chain effectiveness may be influenced by the interaction of multiple factors, and the calculation results may be unstable.

The BP neural network model is a multi-layer feedforward neural network that can explore the underlying patterns from massive complex and fuzzy data, and make corresponding speculations. It is particularly suitable for risk control in supply chain finance. Therefore, the application of BP neural network model in supply chain finance risk control is proposed. Establish a BP neural network model and use a multi-layer feedforward neural network with error backpropagation algorithm to perform dimensionless processing on various control indicators. Clearly identify the specific types of risks, allocate risk weights for supply chain finance, and identify the characteristics of supply chain finance risks. Set up financial risk measurement, combine with BP neural network model, construct a supply chain financial risk management model, and implement risk control.

2. **Financial Risk Control of Supply Chain Based on BP Neural Network Model.**

2.1. **Building BP neural network model.** Generally speaking, the effective control of supply chain financial risk will adopt BP neural network model, which has a three-layer structure, including input layer, hidden layer and output layer [8,9]. The learning ability of BP neural network is to deal with a large number of input variables and output variables, fit the closest mapping relationship, and obtain a nonlinear model. The previous algorithms all need to determine the weight value, mapping relationship and mathematical expression of the input variables in advance, and the BP neural network model can independently complete this process, which is a "black box" model. Due to the backpropagation control mode of the BP neural network model, it can simulate the human nervous system for thinking activities. This algorithm can back propagation and carry out independent training based on the calculation error. It is widely used in various fields. It is a simulation operation system, which can realize independent learning, especially good at data prediction. Continuously adjust the weights and thresholds of the model until the error is within an acceptable range.

When synthesizing risk control indicators, different control indicators usually have different dimensions. In order to eliminate the problem of unified measurement caused by this, a multi-layer feedforward neural network with error back propagation algorithm, namely BP neural network, is used to conduct dimensionless processing for each control indicator. Set all input neurons to x_x $(x = 1, 2, \ldots, x)$ and output neurons to y_y $(y = 1, 2, \ldots, y)$. The specific number of hidden layer neurons is obtained according to the relationship between hidden layer neurons and input neurons.

The weighted sum of neurons of the j input unit r_j is

$$G_{HJ} = \sum_{j=1}^{m} r_j \times D_W \tag{1}$$

In Formula (1), D_W represents the W hidden layer unit. The actual output of hidden layer unit is

$$R_T = S_{nf} \times G_{HJ} \tag{2}$$

In Formula (2), S_{nf} represents the conversion function; The conversion function is a function reflecting the stimulus pulse intensity of the anterior layer input to the posterior node. The main difference of different neural network mathematical models uses different conversion functions, which makes the output of neurons different after obtaining input information, thus having different information processing characteristics. The neural network model structure obtained by learning and adjusting the relationship between neurons at each layer is shown in Figure 1.

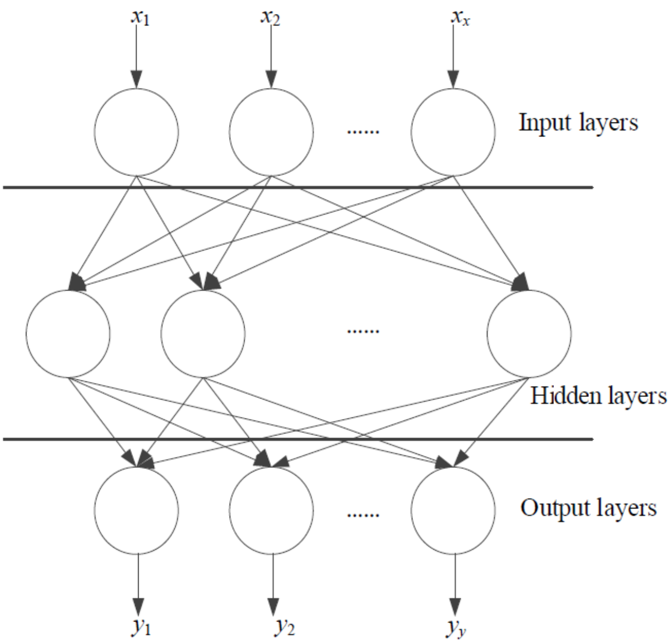

Figure 1. Structure of BP neural network model

According to Figure 1, the weights and thresholds of the BP neural network model are used as the initial population of the adaptive genetic algorithm, and the initial population is coded by the genetic algorithm. Because the training of weights and thresholds of neural networks is a complex continuous parameter optimization problem, the real number coding is used to encode the ownership values between the input layer, hidden layer and output layer and the thresholds of each node into chromosomes.

The characteristics of BP neural network model determine that it can be better applied to supply chain financial risk control [10].

First, the BP neural network model has a strong learning and reasoning ability. It can find out the inherent laws from a large number of complex and fuzzy data in a constantly changing environment, and make corresponding conjectures accordingly. This just caters to the characteristics of more qualitative information and less quantitative information in the supply chain financial risk control [11]. It can analyze and obtain more accurate risk control results from the "soft information".

Second, the BP neural network model has a strong parallel processing mechanism, strong adaptability and high flexibility. Many parameters in the model can be adjusted, and it is good at handling a lot of uncertain information. As an emerging industry, the supply chain financial risk control mechanism is not perfect [12,13]. There are too many uncertainties and incomplete information. The characteristics of BP neural network model fit these characteristics, so it can be better applied to supply chain financial risk control.

Third, the BP neural network model changes the shortcomings of traditional models and avoids the difficulties in model selection and construction. Because the BP neural network model does not require the setting of a certain nonlinear relationship between data, its modeling process is a natural nonlinear modeling process, and the establishment of the model is very convenient and simple, which is suitable for the application of supply chain financial risk control.

2.2. **Dividing the financial risk weight distribution of the supply chain.** In order to control the financial risks of the supply chain, it is necessary to first identify the specific risk types [14,15]. Based on the experience gained from the development of supply chain finance in the past, the risks are divided into four types: operational risk, movable property risk, trade authenticity risk and moral risk of sales collection. Each participant of supply chain finance can provide various information such as transaction contracts and market information during the operation of the supply chain. Then, according to its impact on the supply chain financial business, the corresponding weight is assigned to it. The formula is

$$K_i = \frac{B_i}{X_S - \sum B_i} \tag{3}$$

In Formula (3), K_i represents the importance weight of a risk type i; B_i represents the information entropy of i of a certain risk type; X_S represents the weight classification coefficient. Determine the weight of each risk type according to the above formula to provide a basis for the subsequent extraction of financial risk characteristics of the supply chain.

2.3. **Feature extraction of supply chain financial risk.** After defining the types of supply chain financial risks and their corresponding importance, the characteristics of supply chain financial risks are obtained by combining BP neural network model. Because all the data is in the control room, others can only see their own data, only in the control room, and only the control center can modify the data. Therefore, after determining all kinds of data information on each node of the BP neural network model, we take different ways to obtain the financial risk characteristics of the supply chain. Suppose that there are two partition indicators on the BP neural network model, x_1 and x_2, respectively, and there is a certain dislocation relationship between x_1 and x_2, which can be expressed by the following function:

$$D_1(x_1) = D_2(x_2) \tag{4}$$

In Formula (4), D_1 and D_2 represent the misplaced mathematical expressions of x_1 and x_2, respectively. Based on the above formula, the dislocation difference $\sum x$ of x_1 and x_2 can be found by combining BP neural network model. Based on this value, the maximum correlation coefficient of x_1 and x_2 is further obtained:

$$R_{\max} = \frac{\sum D_1(x_1) D_2(x_2)}{\sum x} \tag{5}$$

In Formula (5), $R_{\max}$ represents the maximum correlation coefficient of x_1 and x_2. Through the above calculation, the $R_{\max}$ calculation results are compared with the risk characteristic threshold. If the $R_{\max}$ value exceeds the risk characteristic threshold, then the obtained characteristics can represent the current supply chain financial risk. The process of extracting the financial risk characteristics of the supply chain is shown in Figure 2.

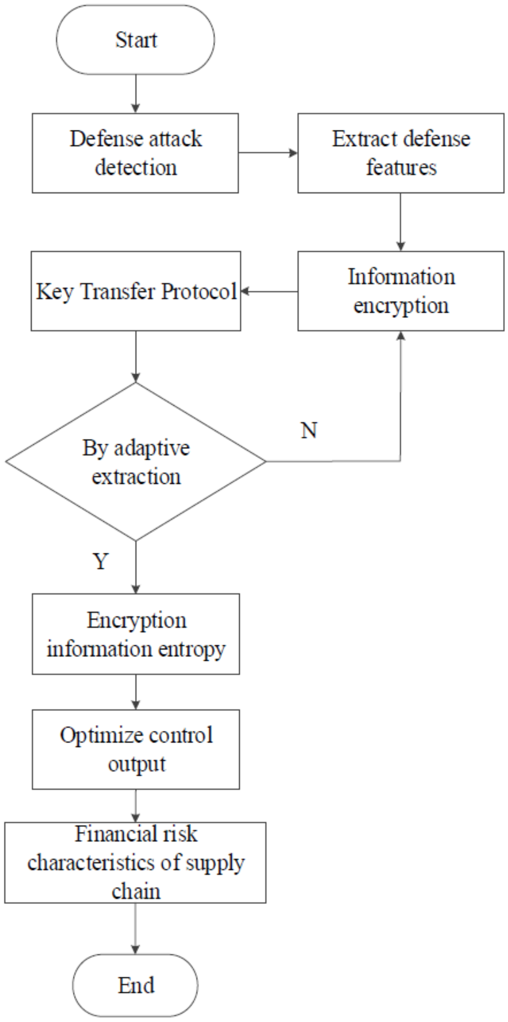

FIGURE 2. Flow chart of extracting financial risk characteristics of supply chain

According to the above ideas, all the partitions that exceed the risk characteristic threshold are summarized to get the supply chain financial risk characteristic set.

2.4. **Supply chain financial risk measurement.** According to the above, after obtaining the financial risk feature set of the supply chain, assume that the mapping of R is a measure of financial risk, and R meets the following conditions:

$$R(x) \geq R(y) \tag{6}$$

In Formula (6), $R(x)$ represents risk in the financial field and reserves in the insurance field; $R(y)$ means the minimum investment required when the investment is risk-free. If R does not meet Formula (6), it means that the risk has translation invariance; If R meets Formula (6), it means that the risk is monotonous. At the same time, the above two basic conditions also have the following characteristics: if risk-free assets are allocated to financial assets, their risks or reserves will be reduced accordingly; According to the performance of BP neural network model, if the return of a financial asset is lower than that of others, then its risk or required reserves are more than those of others. The BP neural network is composed of a large number of interconnected processing units. Through the performance of BP neural network model, information processing and sample learning are carried out, which has a high parallel computing ability.

Each node in the performance of BP neural network model is a processing unit, which is also called neuron. The weighted sum of different input signals received by the neuron is called the net input of the neuron, and the mathematical expression is

$$F_{GH} = \sum_{j=1}^{p} \omega_j \tag{7}$$

In Formula (7), ω_j represents the risk measurement factor. The net input of neurons can use the excitation function of neurons to obtain the activation value of neurons, that is, the response output of neurons is

$$J_K = \lambda_k + \theta_k \times F_{GH} \tag{8}$$

In Formula (8), λ_k represents neuron factor. θ_k represents the activation factor.

In the process of online supply chain financial risk automatic control, there is a nonlinear relationship and dynamic change law between each control index of risk factors and the risk level of risk factors. The neural network can effectively realize the random and complex nonlinear relationship from input to output. The following mainly uses neural network to build the risk automatic control model. Supply chain financial risk measurement mainly includes two functional modules: supply chain financial risk control module and risk elimination module. The risk control module obtains data in the knowledge base and information base, automatically controls the supply chain financial risk, and forms the corresponding supply chain financial risk report based on the control data. The risk elimination module conducts risk reduction through risk control data to form a risk reduction result system report. The supply chain financial risk measurement structure is shown in Figure 3.

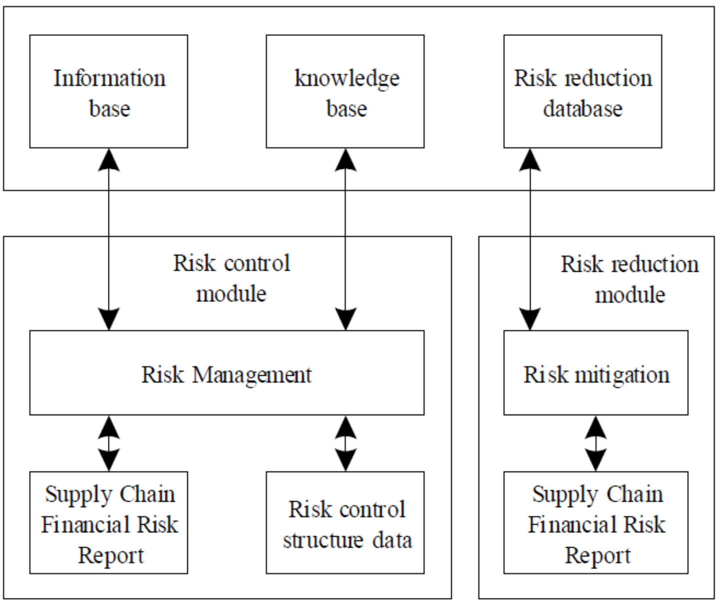

FIGURE 3. Supply chain financial risk measurement structure

3. **Realizing Supply Chain Financial Risk Control.** After determining the measurement structure of supply chain financial risk, a supply chain financial risk management model is constructed by using BP neural network model, and the risk is controlled. Use big data to build enterprise supply chain financial information, analyze enterprise past transactions, performance and other information, and provide reasonable credit lines for enterprises. A large number of BP neural network models are used to analyze customers and select appropriate bank credit to effectively control risks. The calculation formula is

$$H_X = A_a \times B_b \times C_c \times J_K \tag{9}$$

In Formula (9), A_a represents the data of previous transactions; B_b represents the performance; C_c represents credit line. The BP neural network model is used to link the data to ensure the authenticity of the transaction. Combined with the Internet of Things technology, we will monitor the supply chain finance in an all-round way to make its application in the supply chain finance more effective.

Put forward corresponding control strategies for risks. Since all raw materials are manually collated, there will be a certain delay in manual input, and it is very likely that human errors will occur, leading to malicious tampering of data. Therefore, in order to ensure the authenticity and timeliness of the original materials, as well as the automatic generation and real-time feedback of orders and other materials, it is necessary to ensure the authenticity and reliability of the original materials before uploading. Use intelligent sensors to identify commodities, track them in real time, and feed back real-time data to users. The Internet of Things technology can effectively reduce the possibility of forging information. The BP neural network model is used to encrypt and save the real-time transaction information of each link in the Internet of Things. Once a transaction dispute occurs, it can be traced and collected. The combination of the Internet of Things and BP neural network model will greatly improve the authenticity of the transaction information in front of the chain, thereby reducing the financial risk of the entire supply chain.

As BP neural network is more suitable for quantitative data, it lacks the corresponding processing capacity for qualitative index analysis, but the index value of risk factors also has greater uncertainty. The specific process of effectively controlling supply chain risks is shown in Figure 4.

According to Figure 4, the supply chain financial risk is controlled. The specific operation process is as follows.

Step 1: Through the corresponding analysis, the association analysis of assets, threats and vulnerabilities can be carried out to obtain the risk factors of customer information security.

Step 2: Build a risk credibility factor set, namely

$$P = \{p_1, p_2, \dots, p_n\} \tag{10}$$

In Formula (10), p_n represents the risk credibility factor.

Step 3: Control of different risk factors is mainly carried out from the following aspects, such as confidentiality, integrity and availability of customer assets. By dividing the comments of different indicators into m grades, the following evaluation sets can be formed:

$$M = \{m_1, m_2, \dots, m_n\} \tag{11}$$

In Formula (11), m_n represents the risk assessment factor.

Step 4: Determine which areas of expertise are needed based on the specific needs of risk assessment. Invite experts who hold important positions in industry associations, and based on their opinion on different factors, set the membership vector of risk factors to

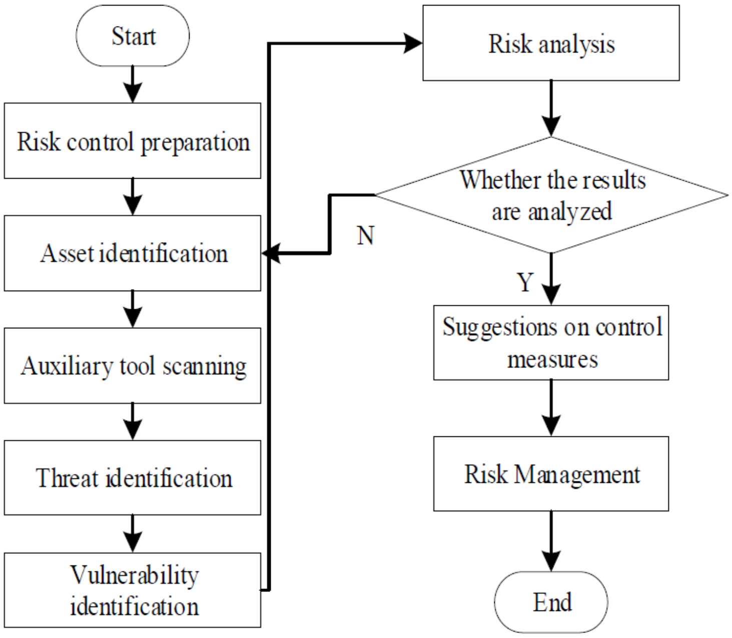

FIGURE 4. Overall control flow chart

the evaluation set as follows:

$$E = \{e_1, e_2, \ldots, e_n\} \tag{12}$$

In Formula (12), e_n represents the risk membership vector factor.

Step 5: The operation mode of supply chain under arbitrary control of different risk factors can be obtained through the calculation of fuzzy transformation:

$$Y_{kl} = P \times M \times E \tag{13}$$

The supply chain operation mode is to take the enterprise development as the core, integrate the logistics information, capital operation information and other information in the enterprise to form a chain structure. Through these information enterprises, all upstream and downstream enterprises, including producers and consumers, can be connected to form an organic cycle system to help enterprises complete the development and value-added work. On the basis of the above analysis, adapt to the development requirements of the era of industrial upgrading, reduce the overall operation cost of the supply chain, optimize the resource allocation on the supply chain, improve the operation efficiency of supply chain finance, so as to realize the new development of supply chain finance and effectively control the financial risks of the supply chain.

4. **Experimental Analysis.** Through the above discussion, a new supply chain financial risk control method is proposed based on the introduction of BP neural network model. In order to verify the application feasibility of this method, the method in this paper is compared with the method in reference [6] and the method in reference [7]. The application feasibility of the three methods is compared by comparing their application effects. The experimental object chooses a financial enterprise in the supply chain as the support, and conducts risk control through three methods respectively for the enterprise. After the control, the enterprise risk is evaluated twice. By comparing before and after the control, the effectiveness of the three methods is compared. In the X64 architecture WIN10 system, the processor is Intel I7, the running memory is 16G, the algorithm is written in C++, and the software environment is CLion. In the experiment, the length of the end-to-end information of the two-tier mobile communication network is 4000, the length of the block

detection sample sequence of information defense is 120, the size of the linear encryption key is 200, the number of nodes in the input layer of the BP neural network is 240, the number of nodes in the middle layer is 200, and the output layer is 30. According to the above parameter settings, and taking into account the objectivity of the experiment, the quantification of the risk level of the enterprise before and after management is achieved through the following formula:

$$L_H = (\alpha \times k_1 + \beta \times k_2) \times Y_{kl} \tag{14}$$

In Formula (14), L_H represents the quantitative result of risk degree; α and β indicate the risk type; Both k_1 and k_2 represent the corresponding weights of the two risk types. The smaller the quantitative value of risk degree, the smaller the risk the enterprise suffers. According to the above formula, the quantitative results of the risk degree of the financial enterprise before and after management are calculated and recorded as shown in Table 1.

Table 1. Quantification of enterprise risk before and after application of the three methods

Different methods	L_H value before management	L_H value after management
Methods in this paper	0.85	0.10
Reference [6] method	0.85	0.45
Reference [7] method	0.85	0.55

In Table 1, the larger the L_H value is, the greater the risk of the enterprise is, and the more vulnerable the enterprise is to financial crisis; On the contrary, the smaller the L_H value is, the smaller the risk of the enterprise is, and the less vulnerable the enterprise is to risk crisis. It can be seen from Table 1 that before the application of the three management methods, the quantification of the enterprise's risk degree was 0.85, but after different methods of control, the enterprise's risk has been reduced to varying degrees. The method in this paper is better than the method of reference [6] and the method of reference [7], and the method in this paper is more effective. The reason is that the method in this paper is more effective after determining the supply chain financial risk measurement structure. Using the BP neural network model, this paper constructs a supply chain financial risk management model and controls its risk. Table 2 gives the comparison results of control results reliability of three different control methods.

Table 2. Comparison of reliability of control results by different methods

Number of tasks/piece	Control result reliability/%		
	Methods in this paper	Reference [6] method	Reference [7] method
10	99.85	86.26	83.97
15	98.14	83.37	81.83
20	98.65	82.13	81.42
25	99.38	84.40	78.20
30	98.47	83.58	75.62
35	97.79	81.89	77.10

It can be seen from the analysis in Table 2 that the control results of this method have the highest reliability; The reliability of control results of the method of reference [6] is next; The method of reference [7] has the lowest reliability of control results. The method in this paper can obtain the highest credibility because it can conduct correlation analysis on assets, threats and vulnerabilities through corresponding analysis, obtain the risk factors of customer information security, establish a risk credibility factor set, effectively solve the problem of risk factor level estimation, improve the accuracy of the entire control result, and at the same time increase the credibility of the control result.

In order to further verify the effectiveness of this method, before continuing to analyze the effect of supply chain financial risk control, the proposed model is tested for relevance to verify the effectiveness of the proposed model for analyzing the effect of supply chain financial risk control. The correlation between the index system of x_1 and x_2 on the BP neural network model and the BP neural network model is adopted. The test results are shown in Table 3.

Table 3. Correlation test results

BP neural network model		0.845
x_1	Reliability factor set	30
	Evaluation set	120
	Membership vector	0
x_2	Reliability factor set	30
	Evaluation set	120
	Membership vector	0

Analyzing the correlation test results in Table 3, the probability value of the BP neural network model is 0.845, the KMO test value is higher than 0.8, the reliability factor set results of x_1 and x_2 test models are both 30, the evaluation set results are both 120, and the membership vector results are both 0, which shows that the results of the two partitions are consistent, and the designed model is verified to be highly effective. The experimental results show that the index system has a high correlation, and the BP neural network model can effectively control the supply chain financial risk.

According to the descriptive statistical results in Table 3, the proposed BP neural network model is used to further analyze the effectiveness of controlling the financial risk of the supply chain. The nonlinear test results of BP neural network model are shown in Table 4.

Table 4. Non linearity test results of BP neural network model

Index name	Value	P value
Operational risk	7.585	0.001
Movable property is a risk	5.647	0.012
Trade authenticity risk	6.835	0.007
Moral hazard of sales collection	4.573	0.015

The experimental results in Table 4 show that all indicators of the nonlinear test results of the BP neural network model meet the significance test results of $P < 0.05$, indicating that the model has typical nonlinear characteristics, which verifies that the supply chain financial risk control is highly effective. The dilemma encountered by the supply chain in its overall operation is the essence of the supply chain financial business, which exists because of its operating mechanism. In order to control supply chain financial risks, it is necessary to find out the causes of supply chain financial risks and possible effective early warning measures from the perspective of supply chain operation, and then improve such measures to help supply chain financial businesses reduce risks and promote the steady development of the national economy.

According to the research results of this paper, it can be concluded that after applying the method proposed in this paper, supply chain finance enterprises can more accurately identify and evaluate risks, thereby formulating more effective risk control strategies. This helps to reduce the risk level of the enterprise and ensure its stable operation. By effectively controlling supply chain finance risks, the method proposed in this paper helps to enhance the reliability and stability of supply chain finance business, and enhances the confidence of investors and partners. This will promote the healthy development of supply chain finance business and provide strong support for the national economy.

5. Conclusion and Prospects.

5.1. Conclusion.

1) Before the application of the three management methods, the quantification of the enterprise's risk level was 0.85, but after the control by different methods, the enterprise's risk was reduced to varying degrees, so the method in this paper is more effective.

2) The method in this paper can obtain the highest credibility, and can perform correlation analysis on assets, threats and vulnerabilities, effectively solve the problem of risk factor level estimation, improve the accuracy of the entire control results, and increase the credibility of the control results.

3) The index system constructed has a high correlation, and the BP neural network model design can effectively control the financial risk of the supply chain.

4) BP neural network model has typical nonlinear characteristics, which verifies that the supply chain financial risk control is highly effective.

5.2. Prospect.

1) In the next step, we need to play a game in the supply chain finance and set various restrictions, some of which are reasonable conditions and some of which are constraints set to simplify the problem. For the latter, we can remove the relevant constraints and make them into variables, which can be considered in the game model, so that we can better make it practical for the participants in the supply chain finance.

2) The Internet characteristics of the supply chain financial risk control platform determine that information asymmetry may provide people with space for fraud. However, in-depth investigation may bring high costs to the supply chain financial risk control platform. Both aspects require an accurate measurement of the control of credit risk influencing factors, and pay attention to the balance between cost and efficiency while strictly reviewing.

3) The supply chain financial innovation is the trend of the times, and the construction of a professional talent team is essential. The next step should focus on strengthening the synergy of all participants in the supply chain, ensuring the standardization and efficiency of business processes, achieving information sharing through the establishment of a special supply chain financial database, learning from the advanced experience of the financial industry in the application of relevant technologies, so as to develop a supply chain financial risk control model suitable for market operation.

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