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Research Article

Predicting the Investment Risk in Supply Chain Management Using BPNN and Machine Learning

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The present work is aimed at solving the investment risks in the supply chain management (SCM) process of enterprises. Therefore, the Back Propagation Neural Network (BPNN) algorithm, logistic regression analysis, and other related theories are used for the risk prediction analysis of supply chain samples. Firstly, 40 pieces of supply chain training data are collected as research samples. Secondly, the examples are trained using the BPNN algorithm. Meanwhile, a logistic regression model is constructed based on Principal Component Analysis (PCA). Finally, the two models conduct risk prediction on the test samples. The results indicate that the BPNN model can effectively predict various risks in the SCM process. It achieves an excellent evaluation effect of single risks, consistent with the actual results. Still, there are some deviations between the prediction results and the actual results of mixed risks. When the significance P value is more than 0.5, the sample is predicted to be of high risk. When it is less than 0.5, the sample is predicted to be of low risk. The prediction accuracy of the logistic regression model is as high as 92.8%, demonstrating brilliant applicability and popularization in the investment risk prediction of the supply chain. The BPNN algorithm and logistic regression model can precisely predict the investment risk in SCM and provide a reference for the improved SCM and the sustainable and stable development of enterprises in the supply chain.

1. Introduction

1.1. Research Background. With the development of science and technology, market competition is becoming even more dynamic and globalized. The supply chain faces increasingly fierce competition in the modern market [1]. However, the supply chain of each industry is affected by a variety of factors. The risk prediction in the supply chain management (SCM) process can offer vital information for the regular operation of the supply chain [2]. Rapid and efficient risk prediction and analysis of the SCM process will help supply chain managers accurately identify and judge the risks faced by the supply chain. It is also practicable to adopt corresponding risk control strategies to optimize enterprise management and workflow and reduce risks in the process of enterprise investment, guaranteeing the virtuous development cycle of the supply chain [3, 4].

1.2. Literature Review. Some scholars have employed the Back Propagation Neural Network (BPNN) to evaluate the risk of specific links in the supply chain. Jeong et al. believed that the BPNN risk prediction model dramatically improved the work efficiency in product logistics transmission and ameliorated problems, such as missed and wrong shipments [5]. Shao et al. analyzed fruit and vegetable production, logistics, and sales risk indicators through the BPNN model. They suggested that the sales were a precarious link, which significantly impacted the overall management process of the supply chain; there were also certain risks in the logistics link [6]. Jiang et al. established a risk index evaluation system by sampling the supply chain data of enterprises. They also built a logistic regression model based on PCA to predict the risk of supply chain variables faced by enterprises [7]. Zheng et al. used the primary effect model to evaluate the influencing factors of logistics enterprises. They deemed that the logistic regression analysis results would be affected by the deviation of sample data [8]. Liu et al. reported that the additives added to product processing could seriously increase the risk to the supply chain. Hence, the authors established a corresponding BPNN model for risk prediction

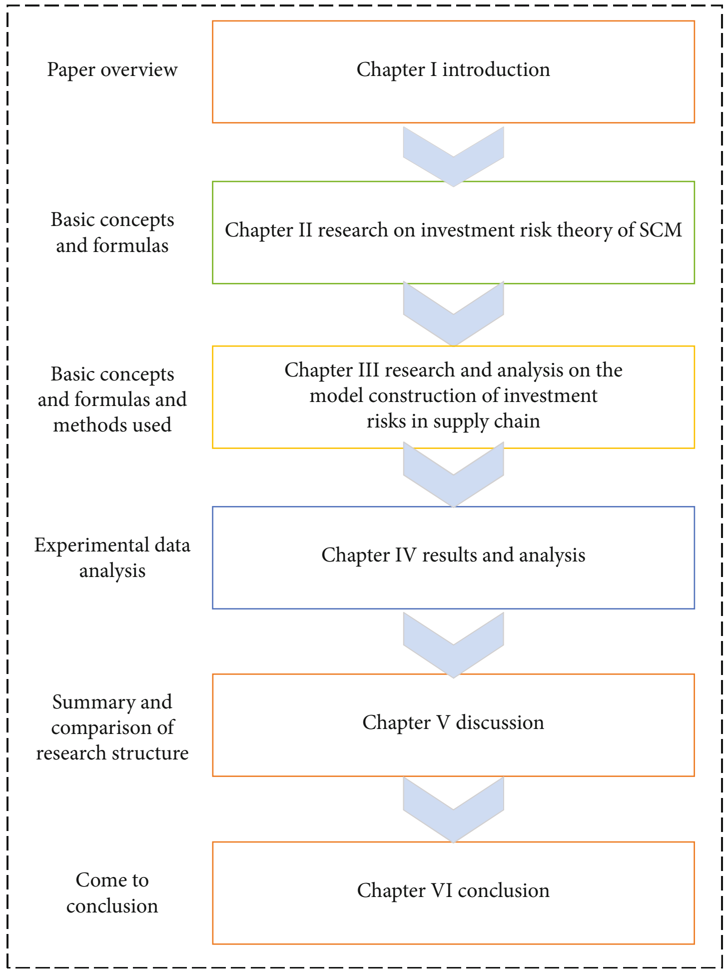

Figure 1: Organizational structure.

[9]. The existing works reflect many factors forming the investment risk of SCM and a remarkably high correlation between various factors, resulting in a lot of overlapping information. The BPNN structure and logistic regression model have advantages in analyzing complex data of a large volume and poor independence. In the related studies listed above, the first few authors mainly studied the industrial SCM from the perspective of logistics enterprises. The latter scholars applied the BPNN and logistic regression model to discuss investment management risks. They all put forward individual opinions from different angles with a certain systematicness. The downside of these studies is that they are limited to a small range of industries and lack certain universality. In addition, the research results are generally more descriptive in words than in data.

1.3. Research Questions and Objectives. This paper collects forty groups of supply chain training samples and ten groups of supply chain test samples for risk forecasting. Specifically, the principal indicators are selected for screening and analysis; the logistic regression model is established based on PCA to optimize the risk indicators; the BPNN model implements risk prediction on these indexes. Risk identification and evaluation of various risk indicators in the SCM process could clearly understand different risk types and levels. It can help enterprises involved in the supply chain improve their awareness of risk management and provide a reference basis for risk prediction and evaluation. It can also provide an effective early warning plan for SCM to reduce investment risks in the supply chain. Figure 1 reveals the organizational structure of the research reported here.

2. Research on Investment Risk Theory of SCM

2.1. SCM. SCM originates from logistics management. As the logistics industry develops, the vertical integration model has become the logistics industry's trend, yet it does not expand the research scope of logistics management. The value chain concept gradually appears under enterprises' collectivized and globalized advancement. On this basis, supply chain theory has gradually formed combined with resource sharing and information interaction among enterprises [10–12]. Scholars worldwide have done many studies on the risk prediction of the supply chain and proposed some common risk evaluation methods. (1) Fuzzy comprehensive evaluation method: it calculates the fuzzy relationship based on the weight of each index and the fuzzy matrix of the prediction object and judges the prediction object using a specific evaluation model combined with the function of each index [13]. (2) Analytical hierarchy process: it decomposes the relevant factors affecting the prediction results into different levels such as objectives, methods, and criteria, then makes qualitative and quantitative analysis, and finally obtains the decision-making method [14]. (3) Grey system theory: aiming at the sample system with low information accuracy, it comprehensively evaluates the risk indicators during SCM by determining the standard weight, evaluation standard, sample matrix, the grey evaluation coefficient, grey evaluation weight matrix, and other methods or steps. (4) Rough set theory: this method mainly uses the correlation among multitudes of historical data to reflect the importance of target attributes. (5) Regression analysis: it refers to a process where a scholar needs to collect a large number of sample data, calculate the regression function among dependent and independent variables based on mathematical statistics, and analyze the relationship between two or more variables. (6) BPNN: this model is established through sample data acquisition and repeatedly trained via the self-learning characteristics to correct the weight and reduce the model error. Then, the connection weight of each layer of the network is analyzed, and a conclusion is drawn [15, 16].

Ricardo Saavedra et al. believed that SCM could systematically coordinate the relationship between departments within the enterprise and related enterprises and improve the work efficiency of departments and economic benefits of enterprises [17]. Kerkkamp et al. reported that SCM was a management mode connecting raw material suppliers, product manufacturers, distributors in goods transportation, logistics personnel, and customers. Besides, information and material flow were continuously repeated [18]. Chkanikova and Sroufe believed that SCM was often a time-based competitive strategy compared with the role of enterprises in a single link. Besides, improving information communication and material turnover efficiency could connect different enterprises, increase cooperation and closeness, and enhance group competitiveness [19]. Pan et al. expounded that from the perspective of overall function, SCM was a comprehensive functional network chain structure mode focusing on the core enterprise using the control of information flow, logistics, and capital flow. It involved the procurement of raw materials, the manufacturing of intermediate products, the manufacturing of final products, and the final product delivery to consumers by the sales network [20].

In short, unlike the visualization concept of the supply chain, SCM is a management mode characterized by strategic cooperation among enterprises at each node. It effectively integrates various resources and maximizes the profits of the whole supply chain system. Because the supply chain system involves multiple participants, links, and objectives, the system is greatly affected by internal and external change factors and often faces management risks.

2.2. Management Risks in Supply Chain. There are many risks in the management process of the supply chain, roughly divided into three categories. (1) Environmental risk: it refers to the risks caused by the external environmental factors of the supply chain, including natural conditions, financial policies, and national laws. (2) Operational risk: it refers to the factors affecting the cohesion and destroying the cooperation of enterprises in the operation process, including information processing, agreement risk, and profit priority. (3) Internal management risk: it indicates the possible problems of each link and enterprise involved in the operation of the whole supply chain and the impact on the whole network chain, including supply link, manufacturing link, logistics link, and customer demand [21]. This paper only analyzes the internal management risk.

Many influencing factors of investment risk exist because SCM involves multiple enterprises or departments. Risk management of the supply chain is aimed at reducing the risk of the supply chain in general by identifying and managing the risk factors existing in the supply chain links and external risk factors [22, 23].

SCM's structure and involved aspects primarily determine the potential risks. Four leading risk indicators are selected here, and three secondary indexes are chosen for each dimension. The secondary indexes of the supply risk are the order satisfaction rate, on-time delivery rate, and quality qualification rate; those of the manufacturing risk are order completion rate, on-time delivery rate, and product qualification rate; those of the demand risk are product return rate, customer churn rate, and order change rate; those of the transportation risk are interactive inventory rate, safe delivery rate, and on-time delivery rate [24].

Figure 2 displays the SCM process and risk classification.

In Figure 2, there are four main links in the SCM process: suppliers, manufacturers, logistics and transportation, and final customers. Each link involves multiple aspects. Correspondingly, the operation process in each part faces corresponding risks, which will ultimately affect the regular operation of the entire supply chain and increase the risk of investment.

Risk management, an essential part of SCM, refers to the management process of identifying, evaluating, and analyzing various possible index risks. Efficiently predicting, preventing, and controlling risks help accurately deal with hidden dangers, ensure enterprises' regular operation, and minimize economic losses. Enterprises can carry out conventional risk management with detailed overall planning and prejudgment to avoid SCM risks. Figure 3 demonstrates the main links.

As shown in Figure 3, the risk management process of the supply chain mainly includes five links: risk awareness, risk identification, risk assessment, risk treatment, and final inspection and evaluation. Firstly, employees and managers in the supply chain must have a degree of risk awareness and consciously predict and estimate risks in advance. Secondly, they need to investigate and identify the risks and analyze the reasons for the formation of risks through classification. Thirdly, they provide a reference for subsequent processing by quantitatively calculating the risk factors. A series of corresponding measures are taken to control the risk within an acceptable range. Finally, the whole process of risk management is scientifically checked and evaluated. Of course, in the entire process, each link is indispensable

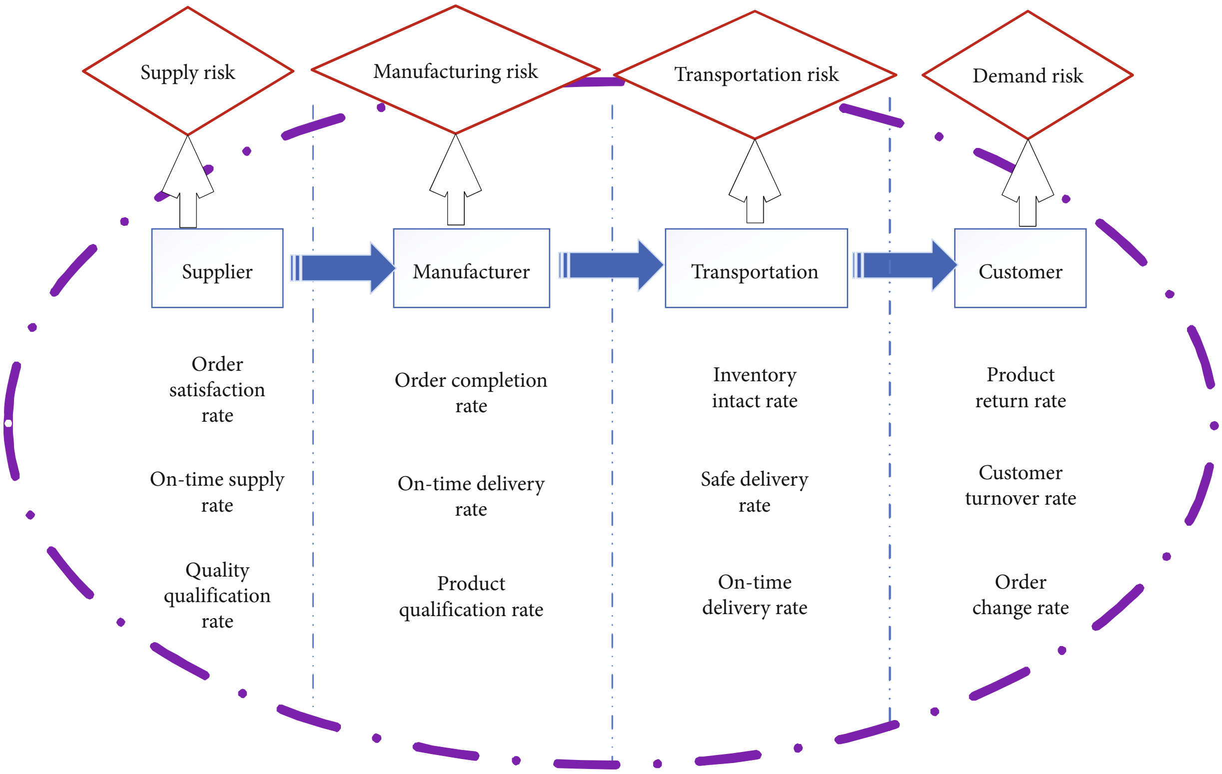

Figure 2: SCM process and risk classification.

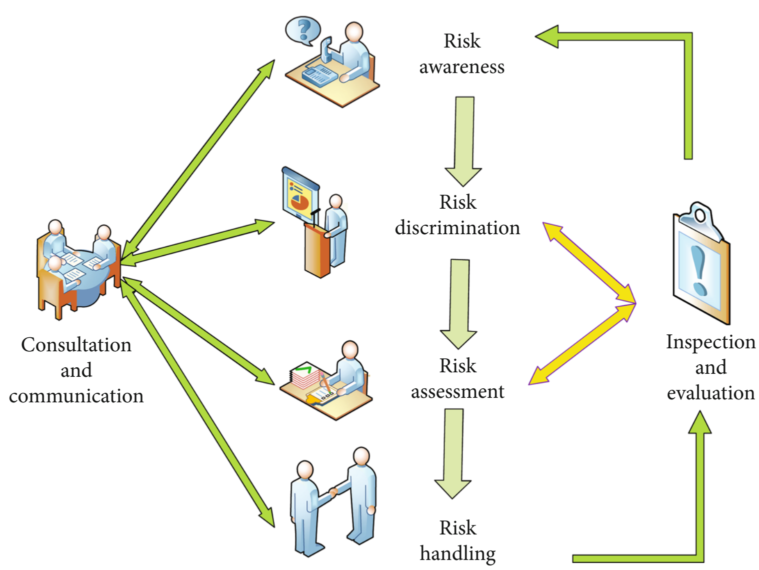

Figure 3: Procedures of risk management in supply chain.

for a complimentary consultation and information communication to form a complete closed loop to deal with the risks of SCM.

2.3. BPNN Algorithm. BPNN is used to conduct risk evaluation. In principle, the network is trained with several evaluation samples representing the sudden risks in a supply chain with known risk types and levels. In this way, it can obtain the empirical knowledge of risk types and levels and the tendency of risk evaluation indicators in the supply chain from the training samples [25]. After the training, the new samples with unknown risks should be input into the network. The network can automatically diagnose the risk types and levels of the new samples according to experience and memory [26].

Here, the standard BPNN with a three-layer topology is used to analyze and evaluate the risks in a supply chain. Figure 4 describes the topology of BPNN.

In Figure 4, the input layer has i neuron inputs; $X = (x_1, x_2, \cdots, x_i)^T$ expresses their signals; there are m neurons in the hidden layer, and $O = (O_1, O_2, \cdots, O_m)^T$ means their signals as well as the input signals of the output layer; the output layer has k neurons, and $Y = (y_1, y_2, y_k)^T$ represents their signals.

Equation (1) denotes the function of the input layer, i.e., the hidden layer of BPNN.

$$o_m = f\left(\sum_{i=1}^{n} v_{im} x_i\right). \tag{1}$$

In Equation (1), f and v represent the activation function and weight of the hidden layer, respectively. Similarly, the relational expression between the output and implicit layers can be expressed as

$$y_k = f\left(\sum_{i=1}^{n} w_{mk} o_m\right). \tag{2}$$

In Equation (2), the meaning of the letters is the same as that in Equation (1). The error between BPNN training prediction and expectation is calculated according to

$$E = \frac{1}{2}\sum_{k=1}^{m} e_k^2 = \frac{1}{2}\sum_{k=1}^{m} (d_k - o_k)^2. \tag{3}$$

In Equation (3), d denotes the expected value, o stands for the predicted value, and e refers to the difference between expected mean value and the target value. The gradient method is used in the training optimization process of BPNN to quickly decrease the weight and reach the optimum:

$$\begin{aligned} \Delta w_{jk} &= \eta \delta_k^0 y_j = \eta (d_k - o_k)^2 o_k (m - o_k) y_j, \\ \Delta v_{jk} &= \eta \delta_k^y x_i = \eta \left(\sum_{k=1}^{m} \delta_k^0 w_{jk}\right) y_j (m - y_i) x_i, \end{aligned} \tag{4}$$

where η and δ represent the learning rate of BPNN and error signal factor, respectively. The remaining letters have the same meaning as in the above equations.

2.4. Logistic Regression Analysis. The logistic regression model is extensively used and has penetrated the fields of medicine, economics, biology, and engineering technology. On the one hand, the logistic regression model can mine the internal information hidden in the data and measure the dependence between explanatory and response variables. On the other hand, it can predict or provide a priori information for decision-makers to make accurate decisions [27].

Let the distribution function of random variable X be

$$F(x, \mu, \sigma) = \frac{1}{1 + e^{-(x-\mu)/\sigma}}, \quad -\infty < x < \infty. \tag{5}$$

In Equation (5), when $-\infty < \mu < \infty$ and $\sigma > 0$, X is said to obey a univariate logistic distribution with parameters μ, σ. μ is called the location parameter of the distribution, and σ is called the scale of the distribution parameter. At this time, the density function of X is defined as

$$f(x, \mu, \sigma) = \frac{e^{-(x-\mu)/\sigma}}{\sigma\left(1 + e^{-(x-\mu)/\sigma}\right)^2}, \quad -\infty < x < \infty. \tag{6}$$

The variable Y is set to be a random variable of two categories. $Y = 1$ and $Y = 0$ indicate the occurrence and nonoccurrence of the events, respectively. The binary logistic regression model is used to describe the relationship between Y and covariate $X = (X_1, X_2, \cdots, X_m)^T$. Equation (6) illustrates the form of the binary logistic regression model.

$$P(Y = 1|\mathbf{x}) = \frac{e^{g(\mathbf{x})}}{1 + e^{g(\mathbf{x})}}. \tag{7}$$

In Equation (7), there is

$$g(\mathbf{x}) = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m, \tag{8}$$

where β denotes the risk probability of the supply chain. The present work mainly adopts the logistic regression model with two classifications shown in Equation (7).

PCA tries to regroup many original indicators with specific correlations (such as P indicators) into a new set of unrelated comprehensive indicators to replace the original indicators [28]. It is a multivariate statistical method to investigate the correlation between multiple variables. It explores how to reveal the internal structure of various variables through a few principal components. In other words, it derives a few main features from the original variables to retain as much information of the original variables as possible and keep them independent. Mathematically, a linear combination of the original P indexes is usually used as a new comprehensive index [29].

3. Research and Analysis on the Model Construction of Investment Risks in Supply Chain

3.1. Model Construction Based on the BP Neural Network. Here, 40 supply chain training samples are used to repeatedly test the BPNN model. There are i ($i = 12$) secondary indexes under the top four leading risk assessment indicators in the input layer and m secondary indexes in the hidden layer, which is finally determined by the test results. The output layer has five main risk evaluation indicators: supply, manufacturing, demand, transportation, and risk levels. Based on the BPNN algorithm, Equation (9) illustrates the relationship between the number of training samples and the number of neurons in each topology layer, i.e., the number of layers.

$$N = 1 + O_m \times \frac{x_i + y_k + 1}{y_k}. \tag{9}$$

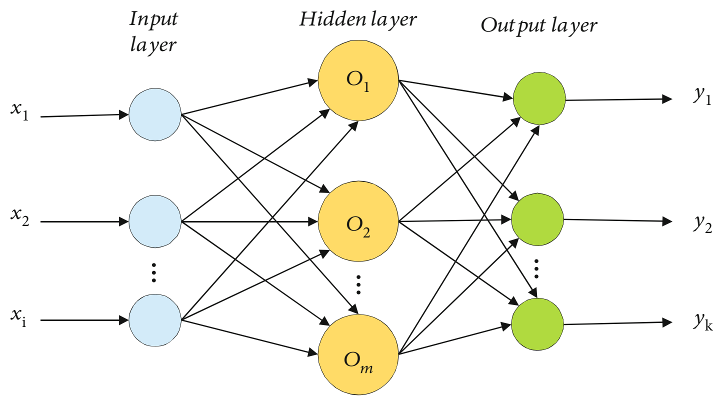

Figure 4: Topology structure of BPNN.

Table 1: Sample variable regression analysis.

Project	Main indicators	Intercept
Regression coefficient (*B*)	1.257	-1.446
Standard error (S.E.)	0.632	0.693
Wald	4.332	4.361
Degree of freedom	1	1
Significance (*P*)	0.035	0.028
OR	3.421	0.256
Confidence interval (E.N.) 95%		
Lower limit	1.045	
Upper limit	11.769	

In Equation (9), N denotes the number of training samples, x_i refers to the number of input layer nodes, y_k stands for the number of output layer nodes, and O_m represents the number of hidden layer nodes.

Symbols represent the output results of indicators in the BPNN model. Among the top four indicators, 1 represents risks, and 0 represents nonrisks; among the risk level indexes, 0 represents the level with nonrisks, and 1, 2, and 3 indicate low-, medium-, and high-risk levels, respectively.

3.2. Construction of Logistic Regression Model. Forty supply chain training sets are selected as the data samples. The logistic prediction model is constructed according to these samples. The contribution of its risk indicators to the supply chain is scored, with the range set to 0-100. 0 represents that the leading indicators are not at risk, 1 means that the leading indicators are at risk; 100 demonstrates that the risk is exceptionally high. The greater the value, the higher the risk level. Besides, classified forecasting is conducted on ten supply chain test samples. The logistic prediction model is designed as Equation (10), and the significance segmentation point is 0.5. When the significance P value is larger than 0.5, the sample prediction is of high risk; when the significance P value is less than 0.5, the sample is predicted as low risk.

SPSS analysis is conducted on the data of four main risk indicators (supply risk, manufacturing risk, demand risk, and logistics risk). The analysis results demonstrate that the risk probability of the main indicators exceeds 85% of the total risk. The logistic model analyzes the values of the main indicators. The significance of the result variables is summarized in Table 1.

Table 1 illustrates that the P value of the main indicators is 0.035 and the P value of the intercept is 0.028, both meeting the test criteria, i.e., less than 0.05. Equation (10) manifests the logistic regression prediction model.

$$P = \frac{e^{(-1.453+1.248F_1)}}{1 + e^{(-1.453+1.248F_1)}}. \tag{10}$$

In Equation (10), F_1 represents the contribution rate of the main index to the sample risk.

4. Results and Analysis

4.1. Risk Evaluation and Analysis of BPNN Model for Training Samples. The MATLAB platform is adopted to train the BPNN model. After repeated training data convergence, the actual system error is the same as the target error, reaching 0.002. Five supply chain training samples, A, B, C, D, and E, are selected for regression simulation. The expected values are represented by Aq, Bq, Cq, Dq, and Eq. The output results are shown in Figure 5. The BPNN model values are represented by Am, Bm, Cm, Dm, and Em, and Figure 6 provides the output results.

Figures 5 and 6 denote that the supply, transportation, and demand risks of training sample A are normal in the expected output Aq and the network output Am. However, the output results of the manufacturing risk are abnormal, indicating a threat with a low-risk level and an error of 0.001. The two output results Bq and Bm of the supply risk indicator of sample B show that there is a risk with a high level and an error of 0.0015. Cq and Cm of the demand risk indicator of sample C are abnormal, and the risk level is medium, with an error of 0.00017. Dq and Dm of the five indicators of sample D are completely consistent, and the error is 0. Eq and Em of the demand risk indicator of sample E are abnormal, the risk level is low, and the error is 0.0012. It can be concluded that the final result output by the network model is basically the same as the expected result,

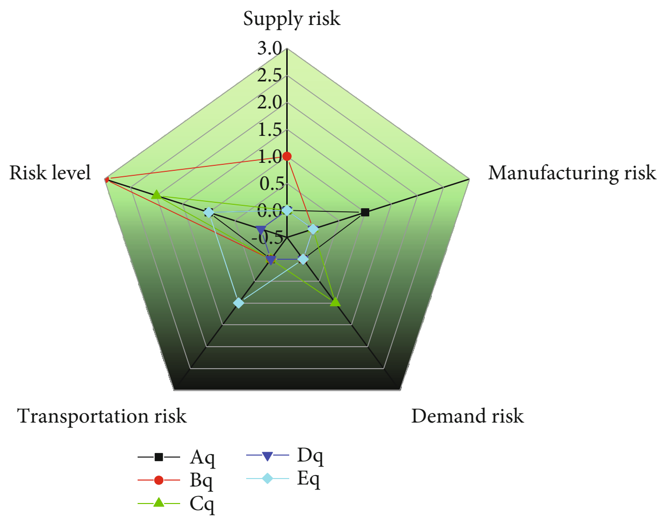

FIGURE 5: Expected output of supply chain training samples.

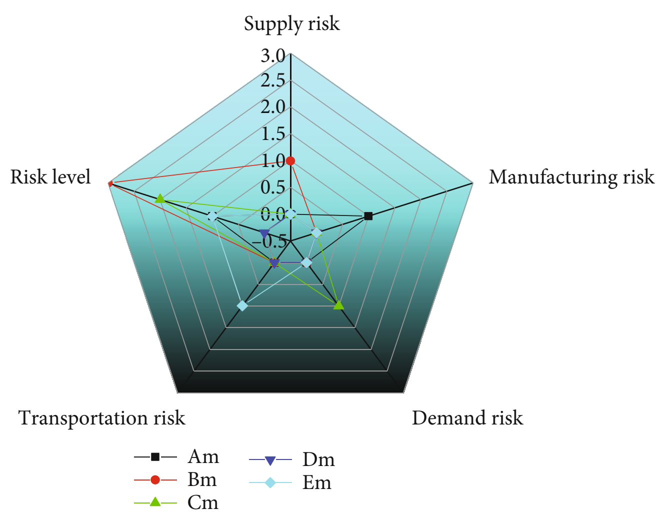

FIGURE 6: BPNN output of supply chain training samples.

and the error is within the set range. In other words, the BPNN model can test the supply chain well.

4.2. Risk Evaluation and Analysis of the BPNN Model for Test Samples. Twelve indicator values of ten test samples, A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1, and J-1, are shown in Figures 7 and 8. The BPNN model is used to compare and analyze the actual results and the predicted results of all indicators, and the results are shown in Figures 9 and 10.

The customer churn rate is the ratio of the number of customers lost to the number of customers for all consumer products or services. Figure 7 suggests that the return rate, customer churn rate, and order change rate of sample E-1 are significantly higher than those of other samples. The customer churn rate is up to 60%. The order change rate of sample J-1 is up to 91%, which has obvious demand risk. The on-time delivery rate of sample D-1 is as low as 40%, and the on-time delivery rate of sample G-1 is as low as 30%. There are proven obvious logistics risks.

Figure 8 denotes that the return rate, customer churn rate, and order change rate of sample E-1 are significantly higher than those of other samples, the customer churn rate has reached 60%, the order change rate of sample J-1 has reached 91%, and there is obvious demand risk. The on-time delivery rate of sample D-1 is as low as 40%, and the on-time delivery rate of sample G-1 is as low as 30%, both of which have apparent logistics risks.

Figures 9 and 10 demonstrate that the BPNN model has a brilliant evaluation effect on the single risk, consistent with the actual results. Still, there are some deviations in the evaluation of mixed risks. The real risk type of sample C-1 is that both supply and manufacturing risks exist simultaneously, and both risks are predicted during the model evaluation. However, the supply risk is at a high level, and the manufacturing risk is at a medium level. The model obtains results that both risks are at a high level. This situation may result from the lack of samples with both supply and manufacturing risks in the training samples, leading to

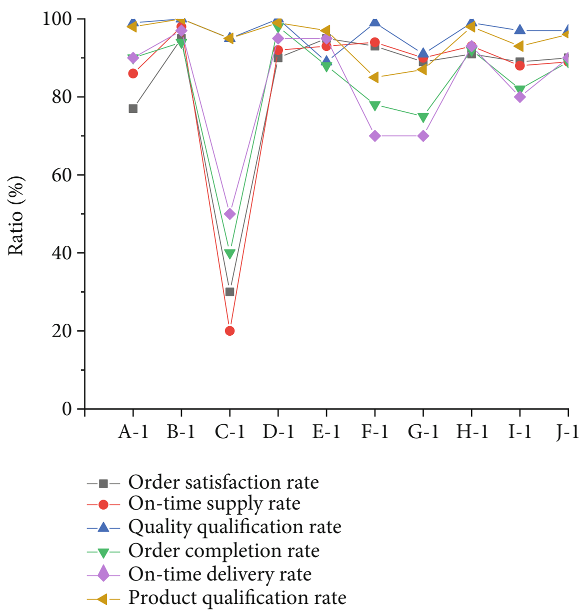

FIGURE 7: Analysis indicators of supply chain test samples.

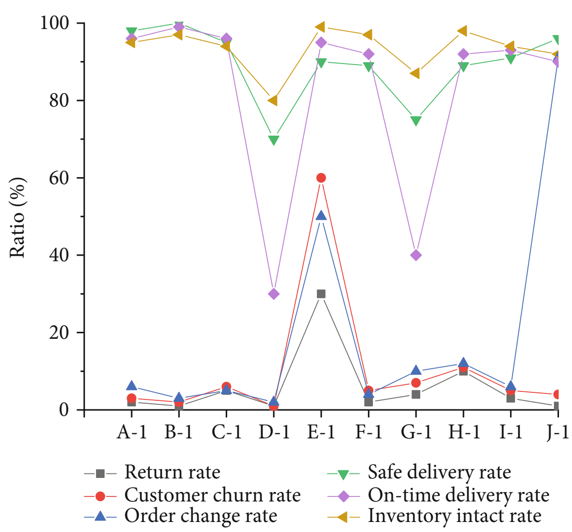

FIGURE 8: Analysis indicators of supply chain test samples.

insufficient model training and imperfect data collection. The demand risk of sample E-1 is very high, and the model makes a proper judgment, consistent with the expected result. For sample G-1, manufacturing and logistics risks exist concurrently, and the predicted risk is at a high level, but the analysis result of the model is a medium risk level. Analyzing the sample index data suggests that the manufacturing and logistics risks in the G-1 samples are inconsistent, and the model deviates in judgment, resulting in inconsistent judgment results. However, the overall model can effectively predict the risk level of each index of the supply chain.

4.3. Risk Evaluation Analysis of Logistic Regression Model of Test Samples. The logistic regression model in Section 3.2 predicts the investment risk of 10 test samples in SCM. Table 2 displays the results.

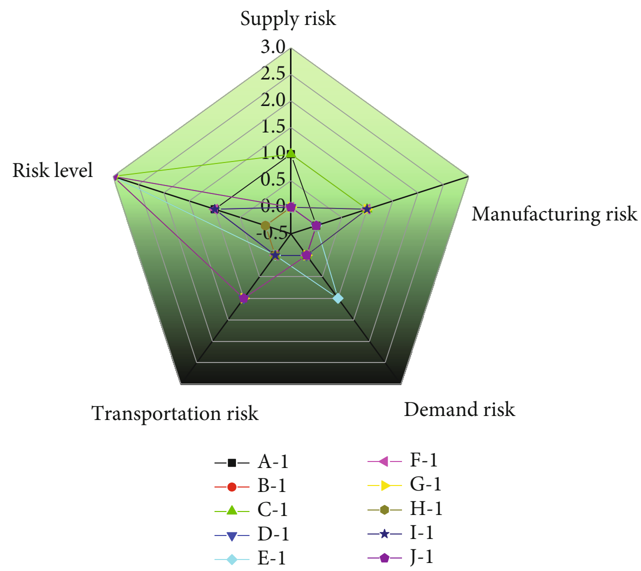

FIGURE 9: Actual evaluation results of supply chain test samples.

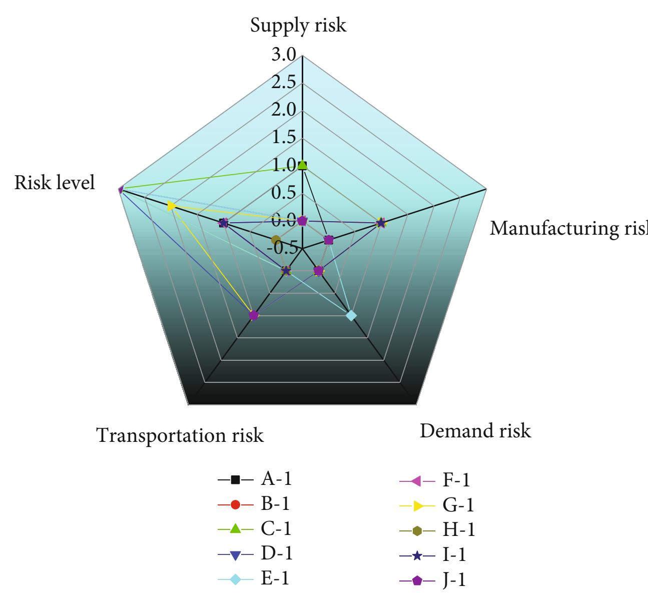

FIGURE 10: Risk evaluation results of the BPNN model for test samples.

Table 2 indicates that when the expected risk is 0, the prediction accuracy of the logistic model reaches 85.7%; when the expected risk is 1, the prediction accuracy of the logistic model is very high, reaching 100%. For ten prediction samples, the overall prediction accuracy has gained 92.8%. The results show that the logistic model has excellent applicability and promotion in investment risk prediction of the supply chain and can provide strong data support for the development of the industry. Mentzer used the risk questionnaire method to study the investment risk of SCM. He found that SCM was systematic and strategic coordination of the functions of traditional enterprises departments within an enterprise and between enterprises from the entire supply chain. The aim was to improve the long-term

Table 2: Supply chain sample forecast results.

Expected value	Estimated value		Number of samples	Correct rate (%)	Total accuracy (%)
	0	1			
0	6	1	7	85.7	92.8
1	0	3	3	100	

performance of the supply chain and each enterprise [30]. From the perspective of environmental analysis, Ma used the financial statement method to predict the risks existing in the supply chain. Ma thought that SCM was based on the core enterprise, through the control of information flow, logistics, and capital flow, starting from the procurement of raw materials, making intermediate products, and final products. Finally, the product was delivered to consumers by the sales network, which connected suppliers, manufacturers, distributors, retailers, and end-users into a whole functional network chain structure model [31].

5. Discussion

The issues of risk investment and risk sharing in SCM are critical, especially for industries with extended supply chains and increasingly uncertain supply and demand. Firstly, this paper collects 40 pieces of supply chain data as research samples and carries out corresponding sample training via the BPNN algorithm. Secondly, the data samples are simulated and trained based on PCA. Finally, the risk prediction is simulated to verify the performance of the models reported here. The main conclusions are as follows. (1) The BPNN model can precisely predict a single risk, and there will be some deviation in evaluating mixed risk. (2) The prediction accuracy of the logistic model is high, about 92.8%. It has good applicability and popularization in investment risk prediction of the supply chain. Bandyopa considered the unequal relationship among enterprises in the supply chain and divided the supply chain enterprises into two categories: core enterprises and partner enterprises. They also utilized the Stackelberg model to discuss the investment decision game between them and compared the results with those of the Cournot model. They concluded that different types of enterprises had different degrees of investment and information sharing, which provided a judgment basis for the investment of supply chain enterprises [32]. Yu et al. constructed the net present value model, internal rate of return model, and Gordon lober model of investment based on the cost-benefit analysis method and the principle of marginal income. The authors emphasized the use of multiple economic models to study investment problems from different angles [33]. Compared with the conclusions drawn by these two scholars, this paper applies the BPNN and logistic regression models to forecast investment risks of SCM and draws the corresponding conclusions through continuous test and sample training. The achievements reported here have specific effectiveness. In addition, the current mainstream neural network algorithm and a regression model are applied, sorting out the theoretical context for the future research on enterprise supply chain and presenting a new research perspective.

6. Conclusion

The investment risk in the process of enterprise SCM is a problem that all companies have to face. The BPNN analysis and logistic regression analysis are carried out on the risk prediction in the process of SCM. The main conclusions are as follows. (1) After a mass of supply chain training samples is collected, the BPNN model is trained using the MATLAB platform by setting four risk indicators (supply risk, manufacturing risk, demand risk, and logistics risk). After repeated training and data convergence, the risk prediction is performed on ten test samples. The results indicate that the BPNN model can effectively predict various risks in the SCM process. The evaluation effect of a single risk is perfect, consistent with the actual results. Still, there are some gaps between predicted and actual results when evaluating mixed risks. (2) A logistic regression model is constructed based on the PCA with 40 training samples. When the significance P value is more than 0.5, the sample is predicted to be at high risk. When it is less than 0.5, the sample is predicted to be at low risk. (3) After analyzing ten prediction samples, the prediction accuracy of the logistic model is very high, attaining 92.8%. In conclusion, the model has excellent applicability and popularization in the investment risk prediction of the supply chain.

Due to limited energy, the range of data is relatively small. Besides, SCM's environmental and overall operational risks are ignored in this experiment. The future study will expand the data size and investigate the risk assessment of environmental factors and operational factors to improve reference value for assessing investment risks in the SCM process.

Data Availability

The raw data supporting the conclusions of this article will be made available by the author, without undue reservation.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Consent

Informed consent was obtained from all individual participants included in the study.

Conflicts of Interest

The author declares that there is no conflict of interest.

Authors' Contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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