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Risk Prediction of Digital Transformation of Manufacturing Supply Chain Based on Principal Component Analysis and Backpropagation Artificial Neural Network

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Abstract Digital transformation of manufacturing is a hot topic among strategic managers of manufacturing companies. The crux of digital transformation lies in the digitalization of manufacturing supply chain (MSC). However, the digital transformation of the MSC is highly uncertain, owing to the dynamic and complex changes of its nodes and structure in response to growing customer demand and fierce market competition. To propel the MSC digital transformation, it is crucial to effectively identify and predict the risk factors in the course of digital transformation. Therefore, this paper attempts to help manufacturing companies in China to successfully switch to a digital MSC. Firstly, the risk sources of the MSC digitization were identified, and complied into an evaluation index system for the digital transformation of the MSC. Next, the principal component analysis (PCA) was performed to reduce the dimension of the original data by revealing the three key principal components, and then the characteristic parameters of risk prediction are selected, so as to simplify the structure of neural network and improve the speed and efficiency of network training. On this basis, a backpropagation neural network (BPNN) was constructed for predicting the risks in MSC digitization. The results of training the model based on some data show that the proposed BPNN model has a good predictive effect. Furthermore, our model was compared with the traditional artificial neural network (ANN) model on a test set. The comparison demonstrates that our model achieved better effect than the traditional model in risk prediction. The results also show that the selected three principal components are reasonable, and the evaluation index system is valuable. The research results provide new insights to the smooth digital transformation of the MSC.

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1. Introduction

With the development of the Internet and information technology, the digital information technology has permeated the manufacturing industry. Digitalization has an immense impact on the market, production conditions, and corporate interactions, forcing companies to change constantly for new competitiveness [1]. As a result, the global manufacturing industry is undergoing a phase of digital strategic changes. Given that China's manufacturing industry is facing with increasingly prominent problems, such as low added value of production, high consumption of resources, low efficiency of resource allocation, high production costs, and difficulty in accurately matching market demands. Every link of the MSC is subject to additional pressure, ranging from the material supply in the upstream to the production in the downstream. In addition, the transportation and other producer services have all been interrupted to a certain extent. The costs of raw materials and processing are both on the rise [2]. Wang and Zheng (2020) pointed out that the original equipment manufacturers in China, which are clustered in Zhejiang and other provinces, encounter difficulties in the production of intermediate products, for reasons like the short supply of raw materials; this situation exerts a huge negative impact on the industrial chain [3]. Hong Wei (2020), from the perspective of supply and demand, suggested improving the MSC coordination ability in the post-epidemic era by optimizing the spatial layout of manufacturing, enhancing SC integration, and promoting the digital transformation in manufacturing [4]. Through case analysis, Wang Jing and Zhao Qilan recognized information sharing and information integration as the keys to the stability of SC, and highlighted the importance of an effective information management system to SC stability [5]. In particular, under the influence of Corona Virus (COVID-19) pandemic, both the supply side and the demand side of China's MSC system are severely impacted and suffer from the multi-directional chain breaking crisis (Liu Yao and Chen Shan, 2020). There is a growing awareness of the significance of MSC stability. It is inevitable to develop a digital SC with the following features based on digital technology, collaborative planning, dynamic contract fulfillment, interconnected customers, smart factories, intelligent supply, and digital development [6]. Driven by digital technology, a new digital form of SC management has gradually taken hold, which is highly dynamic, interconnected, and sharable in real time [7]. Therefore, every manufacturing company should develop a more flexible and stable manufacturing system through the digitalization of SC, which is the basis of modern manufacturing operations.

Digitization makes the SC more virtual and adaptive to information sharing and business collaboration. Through digitization, the resources will be utilized more sustainably, and the decisions on supply and demand will become more effective. However, digitization also brings some negative impacts on the SC. For instance, the complex virtual relationships in and outside the SC, coupled with the complicated cooperation patterns, will expose the SC to new potential risks. In addition, the SC is a complex carrier of logistics with information, capital and business flows, and a theater of multi-level and multi-faceted cooperation between various parties. The complex identities make the SC vulnerable to both the external and internal environments. Risks are ubiquitous in the real world. The risk probability is high in an environment with fast market and technological changes. In short, with the use and update of the new generation of information technology and the collection and collation of the user's big data, due to the emerging new forms of electronic data, the risk in the digital transformation of SC will rise [8]. Moreover, despite the enthusiasm of enterprises for digital transformation in recent years, research shows that the success rate of enterprises' digital transformation is less than one third (McKinsey Global Institute, 2019). This shows that the digital transformation of MSC is difficult and is an innovative process full of risks. To some extent, the digital SC driven by advanced technology is definitely riskier than the traditional SC. What is a worse, Chinese manufacturing company are accustomed to the production-oriented model of development, lacking sufficient experience in digital transformation. As a result, they are bound to meet any new problems and risks in this new industrial transformation. Some scholars have paid attention to the risks of digital transformation. But few have discussed which risks the transformation brings to the manufacturing industry.

To improve the success rate of digital transformation of China's MSC, the paper will combine the theoretical research status of digital supply chain, focusing on the new characteristics of digital supply chain, based on the technology, organization, and environment (TOE) theory, put forward the risk composition diagram for the digital SC. Then, drawing on empirical data, the Backpropagation Neural Network (BPNN) will be employed to predict the digital transformation risks of the MSC. The research results should contribute greatly to the effective management of digital transformation risks.

2. Literature Review

The digital transformation of MSC is the key to the digitization of manufacturing companies. At present, the research on the digital transformation of manufacturing supply chain at home and abroad is still in the primary stage. According to the research objectives, this paper focuses on the following aspects of literature review.

2.1. Connotations of digital MSC

With the dawn of the digital transformation era, the SC in the global market competition becomes highly complex, involving the transaction between multiple parties. To adapt to customer demand, all companies need to develop an SC that is intelligent, agile, and efficient [9]. The digital transformation of the SC focuses on digitizing decision control, operation, lifecycle management, procurement, as well as credit and finance [10]. After the transformation, a digital SC will emerge, in which different activities (e.g., forecast, planning, execution, and decision-making) can be guided by processing big data with artificial intelligence (AI) algorithms [11]. Cecere (2016) defined the digitalization of the SC as the realization of the two-way perception, response and coordination of channel and supplier network using new technologies [12]. The digitalization of SC is an intelligent and efficient process, which improves the supply chain system through technological innovation and creates new value for the organization [13]. In essence, SC digitization is a customer-centric platform. On this platform, data are collected from multiple channels, and their values are maximized in real time. Meanwhile, the customer demand is simulated, matched, sensed, and managed to enhance corporate performance and minimize risks. The framework of digital SC can be divided into digital planning, digital procurement, digital production, and digital logistics [14]. Therefore, this paper defines digital SC as the real-time acquisition of the data on management and decision-making of all business activities of the SC, using digital information technology, and tries to reduce SC risks and improve SC performance through intelligent management and decision-making by intelligent algorithms. Over the years, the operating model of digital SC has shifted from the series model to parallel model. The shift deepens the connections within the company, creating an interconnected community that is always online. Relying on data-driven intelligence, this community boasts end-to-end transparency, and optimal overall decisions [15,16]. In brief, the purpose of digital SC is to make smart decisions, and achieve smart manufacturing. In a digital SC, companies are required to refocus from production to demand, and develop a demand-oriented precision SC based on big data. Such an SC can decipher the rapid changes in consumer demand and the market by collecting and analyzing commercial data, rationalize the positioning and design of products, and make demand forecast and early warning in real time [17].

Generally, the connotation of MSC digital transformation is around the SC relationship structure, the digitalization of supply and demand factors, the digitalization of supply and demand means and the purpose of digitalization, which can be presented as figure1.

Figure 1 shows that the digitalization of various supply and demand resources (manpower, capital, knowledge, culture, etc.) is the basis of the relationship structure of MSC and MSC management digitalization. And the relationship among the three is interactive. Only while all kinds of supply and demand activities are transformed into information flow, capital flow, logistics and technology flow, can management factors be integrated to realize digitalization of management. However, with the rapid development of information technology and the in-depth promotion of digital economy, the MSC is more open and the supply and demand flow is frequent and diverse. The digital operational information surrounding SC will become richer, and at the same time, SC management will also face more new challenges.

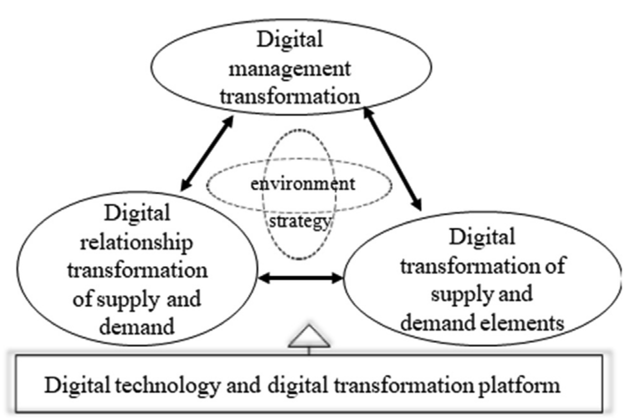

Figure 1 The basic structure of supply chain digital transformation

2.2. *The driving factors of the MSC digital transformation*

The digital SC typically contains ontologies such as network, big data, integrated platform, and intelligence [18]. The transformation to a digital SC relies on technologies in computer network, communication, information, and intelligence. The most representative technologies for the digital transformation of SC include block-chain, radio-frequency identification (RFID), the Internet of things (IoT), and cloud computing. From the perspective of commercial value, these technologies have different digital utilities for and varied impacts on the SC. For example, block-chain could solve the problems of cooperative trust and information sharing in the SC [19]. The RFID can seamlessly collect receipts and share data in real time, effectively reduce the total inventory cost and bullwhip effect, and boost the inventory turnover and transparency of the SC [20]. Cloud computing can acquire a massive amount of various information at low cost and high quality, renovate business model, management method, and management strategy, and lead to a simple, fast, and efficient service model of the SC. Together, these digital technologies will allow companies to satisfy customer demand through real-time analysis on SC planning, acceleration of logistics turnover, and rationalization of inventory level [21]. From the perspective of technology driving, this paper argues that technology, organization, and environment (TOE) theory is more suitable to analyze the influencing factors of MSC digital transformation.

2.3. *Discussion on the Risks of Digital Transformation of MSC*

At present, there are few researches on risk management of a digital or a smart SC at home and abroad [22]. Only a few of the literature presents some risk awareness from the perspectives of data security, SC robustness, and digital technology. Digital information flow and integration systems have higher requirements for data quality [23]. Digital transformation risks are highly concentrated on data security [24]. In the case of poor decision-making, imperfect sharing mechanisms and complex SC networks, digital SC systems are prone to non-technical instability [25,26]. Although digital technology has the effect of reducing the "bullwhip effect" of the SC, the nodes on the chain will also have technological paradoxes due to poor technical capabilities and corporate capabilities [27,28]. Therefore, the digital transformation of MSC often has false or inefficient transformations.

In general, scholars at home and abroad have reached a consensus on the concept of digital SC, and the theoretical perspective has gradually enriched. However, compared with the research on enterprise digitalization, the literature on the digital transformation of MSC is not only less, but the research content also needs to be expanded. The research on the risks of the digital transformation of the chain should be the focus of the next stage of research.

3. Theoretical Foundations

3.1. *TOE Theory*

On the basis of the classic technology acceptance model and innovation diffusion theory, the Technology Organization

Environment (TOE) theory proposed by Tomatzky holds that the adoption of an innovative technology by an organization is mainly affected by three factors: technology, organization and environment [29,30]. Most of the researches focus on the internal and external factors of TOE and the characteristics of technology itself, which are widely used in the analysis of influencing factors of organizational technology adoption in different information system fields [31,32]. In the TOE theoretical framework, technical factors usually include safety, compatibility, relative superiority, ease of use, and so on [33]. Among them, organizational factors usually refer to organizational characteristics such as organizational strategy, organizational culture, organizational structure and organizational scale [34]; Environmental factors mainly refer to the government environment, industry situation, competition situation, etc [35]. The theoretical framework of TOE has good adaptability and explanatory power, and can flexibly adjust the corresponding decisive factors according to the specific research objects [36]. Therefore, it can be used not only in the analysis of influencing factors of technology adoption, but also in the analysis of effective management factors.

Similarly, the TOE theory can be adopted to identify the factors affecting the digital transformation of MSC. Drawing on this theory, Jin Jun et al. identified a number of factors that greatly affect the digital transformation of companies: production capability, mastery of information system, organizational structure, senior management, cooperation resources, industry features, market structure, and government regulation [37]. On the mechanism of action, the digital transformation of MSC is also influenced by transaction cost, demand variation, value distribution, and labor boundaries [38]. Overall, the study on the digital transformation for MSC based on the TOE theory can be effectively mined. As a result, this paper should decide the success/failure factors of MSC digital transformation by the TOE theory.

3.2. Risks of digital MSC

At present, there are few researches on risk management of digital or intelligent SC at home and abroad [36]. Accordingly, in-depth researches on digital risk prediction of MSC are less and there is no yet a consensus on what factors affect the digital transformation of manufacturing. This paper analyzes the risk incentives of MSC digital transformation based on TOE theory.

According to the TOE theory, technology, organization, and environment are the three primary risk sources of MSC transformation [39]. Once digitized, the SC will face a higher risk of privacy leak, due to its openness and share ability. This risk increases with the expansion of business and the complication of cooperation. Digital technologies are a necessary but not sufficient condition for a successful transformation of SC. To transform the SC successfully, the crux is to ensure the consistency of the applied technologies and the business purpose of the company. For instance, if the business strategy has a special demand for AI, and if the AI can bring an added value not seen in other companies, then it would be reasonable to implement the AI technology [27]. Big data-based smart logistics technology applies well to information sharing, resource-based collaboration, and SC integration [40]. Many smart SCs, which integrate blockchain, smart contract, and IoT, meet the requirements on trust, regulatory traceability, and data privacy [41]. Strategically, the information exchange between divisions or companies is affected by the coordination ability of each SC company, and the strategy consistency among companies. If the two factors are not desirable, the divisions or companies would be unable to share information timely, creating information risks. Conceptually, the traditional SC concepts like internal alliance and external competition could no longer support the development of modern companies amidst fierce market competition. These outdated concepts would hinder the transformation and upgrading of the SC [42]. At the same time, partners also need to achieve strategic consistency, such as the strategic matching of cooperation strategy, information demand and technology, and the matching of technology adoption among partners. The digital transformation of production relations is also reflected in the digital transformation of contract governance. The core of the digital transformation of contract governance is the formation of technology contract[43]. Technology contract refers to the fact that digital technology contains governance features, forms implicit codes of conduct, and constitutes a neutral third-party contract that does not contain subjective judgment of human beings. The combination of technical contract, formal contract and relational contract can effectively improve governance efficiency [44]. Moreover, the risks of digital SC are associated with some environmental factors, that is, the factors of the macro environment for the company to operate. These factors include but are not limited to: government environment (e.g., policy, institutional environment, and government support), industry situation (e.g., market structure, and industry environment), and competition status (e.g., customer relationship, and competitor relationship) [36]. To promote the digital transformation of manufacturing, China has released the Made in China 2025 Strategy. Since China steps up its support to this transformation, this paper chooses to ignore the risk of lacking policy support, but focus on risk factors like market volatility, development space, and supply-demand uncertainty.

Through the above analysis and the risk measurement items in some references, the risks of the digital transformation of MSC in China were broken down into 12 indicators in four dimensions (Table 1), laying the basis for empirical analysis.

4. Methodology

4.1. Principal component analysis (PCA)

The PCA is one of the most popular methods for dimensionality reduction. It aims to replace massive correlated variables with a few unrelated variables, without sacrificing much of the information in the initial variables. The unrelated variables are called principal components, which are linear combinations of observed variables [56]. The PCA algorithm adopted in this paper can be implemented in the following steps:

Step 1. Standardize the sample data by min-max normalization to prevent the errors arising from the sample size and data scale for improving network training efficiency and network generalization ability. the value of each index of a sample equals the difference between the current value and the minimum value, divided by the difference between the maximum and minimum values. Assume that i represents the number

Table 1 Risks of MSC digital transformation

Dimensions	Indicators	Explanation	Literature
Information technology risk (R1)	R11	The lack of information technology guarantee leads to the risk of transformation caused by information distortion or information lag.	[45-47]
	Inaccurate/inefficient SC services (R12)	The lack of information technology guarantees leads to the lack of high quality digital supply and demand services	
	Poor digital integration (R13)	Poor digital technology cannot effectively integrate supply chain resources, leading to the risk of digital transformation.	
Organizational strategy risk(R2)	Weak IT strategy consistency (R21)	Discordant IT strategies among SC partners can lead to a variety of inconsistent digital resource matching and collaboration risks.	[48,49]
	Ineffective knowledge acquisition (R22)	Digital transformation is the process of collaborative knowledge innovation, and organizational strategy has a great impact on the innovative acquisition of organizational cultural knowledge.	
	Low SC robustness (R23)	The cooperation strategy of supply chain determines the cooperation stability of its structure and the smoothness of its digital transformation.	
Environmental risk (R3)	Unstable market environment (R31)	The greater the market volatility, the greater the uncertainty SC faces and the greater the risk of its digital transformation.	[50-52]
	Trust risk (R32)	The more complex the supply chain structure is, the more complex its operation environment is, so the establishment of an effective trust mechanism between partners becomes a key factor affecting its transformation.	
	Bleak prospect of industrial development (R33)	Under the poor industrial environment, the actual power of MSC's digital transformation is greatly reduced.	
MSC management risk (R4)	Ineffective risk prevention (R41)	For potential risks, organizations with strong risk prevention measures will reduce the possibility of risk occurrence.	[53-55]
	Irrational decisions on risk management (R42)	The ability of risk decision-making (such as risk prediction and early warning) directly affects the risk prevention and control ability of an organization.	
	Inability to identify risks (R43)	The capability of risk decision-making (such as risk prediction and early warning) based on digital risk information perception and identification directly affects the risk prevention	

of samples and j represents the number of risk indicators. The mathematical expression of risk data normalization is as follows:

$$R'_{ij} = \left(R_{ij} - R_{ij-\min}\right)/\left(R_{ij-\max} - R_{ij-\min}\right) \tag{1}$$

where, R'_{ij} is the data of the j-th index of the i-th sample after the R_{ij} changed. R_{ij} is the data of j-th index of the i-th before changing. $R_{ij\text{-}min}$ is the minimum value of the j-th index of the i-th sample. On the contrary, $R_{ij\text{-}max}$ is the maximum of the j-th index of the i-th sample.

Step 2. Establish the covariance matrix of standardized samples.

Step 3. Calculate the eigenvalues and eigenvectors of the matrix.

Step 4. Compute the variance contribution rate and cumulative variance contribution rate of each principal component according to the eigenvalues.

Step 5. Select the principal component with the largest contribution rate as the new variable.

4.2. BPNn

The digital transformation of the MSC faces high uncertainties, due to the complex supply-demand relationship in the MSC. The uncertainties add to the difficulty in predicting the risks of MSC digital transformation. On the basis of the PCA, this paper selects the BPNN to predict the risks in the digital transformation of the MSC. This network was selected for the following reasons: with multilayer perceptron (MLP), the BPNN can adapt to and express the nonlinear dynamic environment effectively, and achieve efficient learning and accurate prediction; the prediction accuracy of the BPNN can be further improved through the dimensionality reduction by the PCA [57]. The BPNN is composed of an input layer, a hidden layer, and an output layer. During the operation, the BPNN combines the forward learning and training of inputs with the backpropagation of error data.

Regarding that BPNN has m input neurons X, a hidden layer with n neurons Z, and an output layer with k output neurons Y. The influence of X_i on Z_j is weighted by WZ_{ij}, and the influence of X_i on Y_j is weighted by WY_{ij}.

Then the j_th hidden neuron is calculated as:

$$Z_{\mathrm{j}} = \sum_{i=1}^{m} WZ_{ij} * X_i + c \tag{2}$$

where, c is the deviation constant.

After the input data is processed by the activation function $f(x)$, the output Y_j can be expressed as:

$$Y_{\mathrm{j}} = \sum_{j=1}^{n} WY_{ij} * f\left(\sum_{i=1}^{m} WZ_{ij} * X_i\right) \tag{3}$$

Formulas (2) and (3) are the forward learning and training of inputs. During error backpropagation, the root mean square (RMS) between the actual output and the target output is taken as the error index to find the partial derivatives of each node on the current layer and that on the previous layer. The calculation is performed layer by layer, from the output layer to the input layer. Then, the gradient descent optimization is performed to adjust the connection weights into WZ'_{ij} and WY'_{ij}, and update the deviation constant C. The backpropagation process should be terminated, when the RMS is minimized, or when the maximum number of iterations is achieved.

Fundamentally, BPNN aims to minimize the total error of the network. Here, the fastest descent method is adopted to correct the connection weights, according to the negative gradient direction of the error function [58]. The prominent advantage of the BPNN is that the sample data can be utilized repeatedly, which improves the training and fitting effects [59]. That is why the BPNN was adopted to predict the risks in digital transformation of MSC.

5. Design of Evaluation Index System

5.1. Sample data acquisition

This paper designs a questionnaire on the digital transformation risks of MSC based on Table 1. Third-party research firms were entrusted to conduct the questionnaire survey in some large and medium-sized manufacturing companies in China. Each item in the questionnaire was evaluated against the Likert 5-point scale. A total of 225 questionnaires were distributed, and 87.6% (197) of them were collected and found to be valid.

5.2. PCa

For the original sample data, the Cronbach's alpha was 0.832, a sign of high reliability; the Kaiser-Meyer-Olkin (KMO) statistic was 0.863, close to 1; the statistic of Bartlett's test of sphericity was 995.389; the P value was 0, lower than the significant level. Overall, the original sample data are suitable for PCA. Then, the selected risk indices were subject to reliability and validity analysis on SPSS 22.0. Table 2 presents the Eigen Value, variance contribution rate, and cumulative variance contribution rate of each principal component.

Table 2 Results of reliability and validity analysis

Principal component	Eigen value	Variancecontribution rate	Cumulative variance contribution rate
1	4.618	38.482	38.482
2	1.866	15.550	54.033
3	1.321	11.005	65.038
4	.727	6.062	71.100
5	.642	5.353	76.453
6	.587	4.888	81.341
7	.511	4.261	85.602
8	.480	4.004	89.605
9	.402	3.349	92.954
10	.356	2.963	95.917
11	.325	2.709	98.627
12	.165	1.373	100.000

As shown in Table 2, the Eigen Values of the first three principal components were all greater than 1, and the cumulative variance contribution rates of them totaled 65.038%. Thus, the original data on the 12 indices could be reduced into three principal components. Through the rotation by Varimax with Kaiser Normalization, the coefficient matrixes of the principal components were obtained (Table 3).

According to the matrix (Table 3) and Eigen-values, the three principal components can be expressed as:

$$\begin{aligned} Risk1 = & -R11^{*}0.049 + R12^{*}0.267 + R13^{*}0.291 + R21^{*}0.044 \\ & + R22^{*}0.031 + R23^{*}0.735 + R31^{*}0.883 + R32^{*}0.838 \\ & + R33^{*}0.72 + R41^{*}0.162 + R42^{*}0.209 + R43^{*}0.848 \end{aligned} \tag{4}$$

$$\begin{aligned} Risk2 = & R11^{*}0.773 + R12^{*}0.762 + R13^{*}0.745 + R21^{*}0.012 \\ & + R22 * 0.132 + R23^{*}0.2 + R31^{*}0.168 + R32^{*}0.031 + R33^{*}0.24 \\ & + R41^{*}0.712 + R42^{*}0.701 + R43^{*}0.23 \end{aligned} \tag{5}$$

$$\begin{aligned} Risk3 = & R11^{*}0.114 + R12^{*}0.066 + R13^{*}0.107 + R21^{*}0.832 \\ & + R22^{*}0.807 + R23^{*}0.026 + R31^{*}0.019 + R32^{*}0.007 \\ & + R33^{*}0.066 + R41^{*}0.064 + R42^{*}0.015 + R43^{*}0.047 \end{aligned} \tag{6}$$

In this way, the authors obtained the BPNN inputs for risk prediction.

6. Design and Application of PCA-Based BPNN Model

6.1. BPNN model design

The standardized index data were taken as the inputs to the BPNN, with the comprehensive transformation risk as the output layer node. The number of hidden layer nodes is generally calculated by [60,61]:

$$(m+n)/2 \leqslant L \leqslant \sqrt{(m+n)} + c \tag{7}$$

where, m, n, and L are the number of input layer nodes, that of output layer nodes, and that of hidden layer nodes, respectively; c is a constant between 1 and 0. Since m = 12

Table 3 Coefficient matrix of the three common factors

Principal Component	Factor1	Factor2	Factor3
R11	-.049	.773	.114
R12	.267	.762	.066
R13	.291	.745	.107
R21	.044	-.012	.832
R22	.031	.132	.807
R23	.735	.200	.026
R31	.883	.168	.019
R32	.838	.031	-.007
R33	.720	.240	.066
R41	.162	.712	-.064
R42	.209	.701	.015
R43	.848	.230	.047

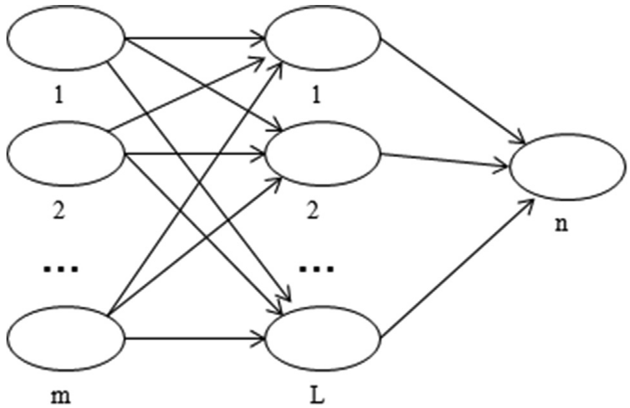

Figure 2 Structural design of BPNN for risk prediction

(the number of risk indices) and $n=1$ (the number of output), the L value must fall between 7 and 14. After repeated network trainings, it was learned that the BPNN had the best overlapping efficiency and training accuracy at $L=7$. As a result, the number of hidden layer nodes was set to 7. Figure 2 shows the BPNN structure for risk prediction.

6.2. Training of BPNN

Based on the 182 valid data on risk indices, our BPNN achieved a training accuracy of 0.000996 at the learning rate of 0.1 and the maximum number of trainings of 50. The accuracy meets the required accuracy level of 0.001. Figure 3 presents the prediction error of our BPNN.

As shown in Figure 3, the prediction error was smaller than 7%, that is, our BPNN realized high comprehensive prediction

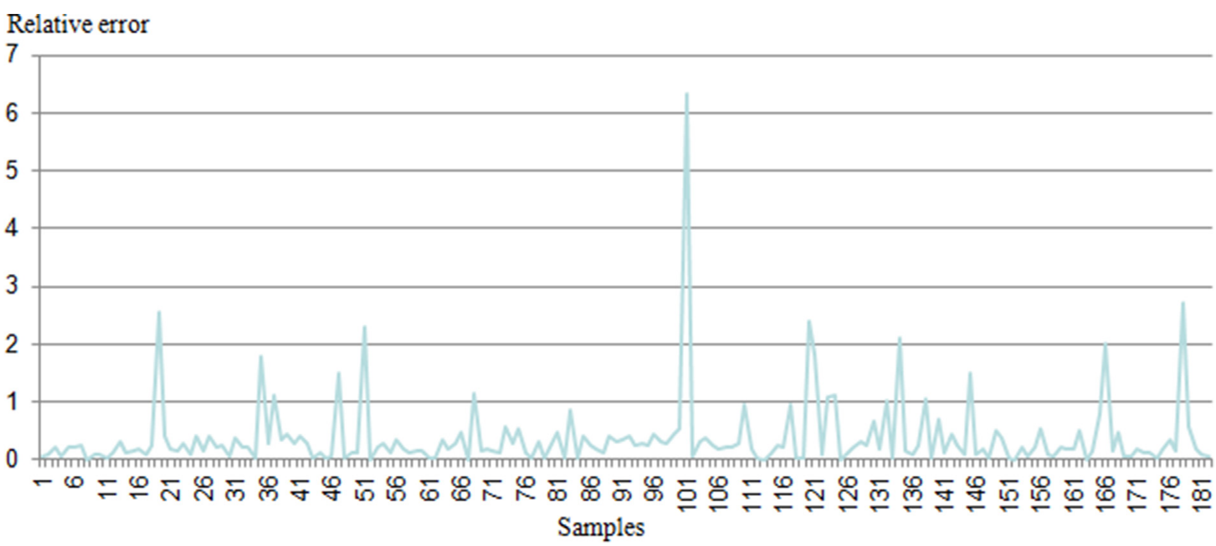

Figure 3 Prediction error of our BPNN

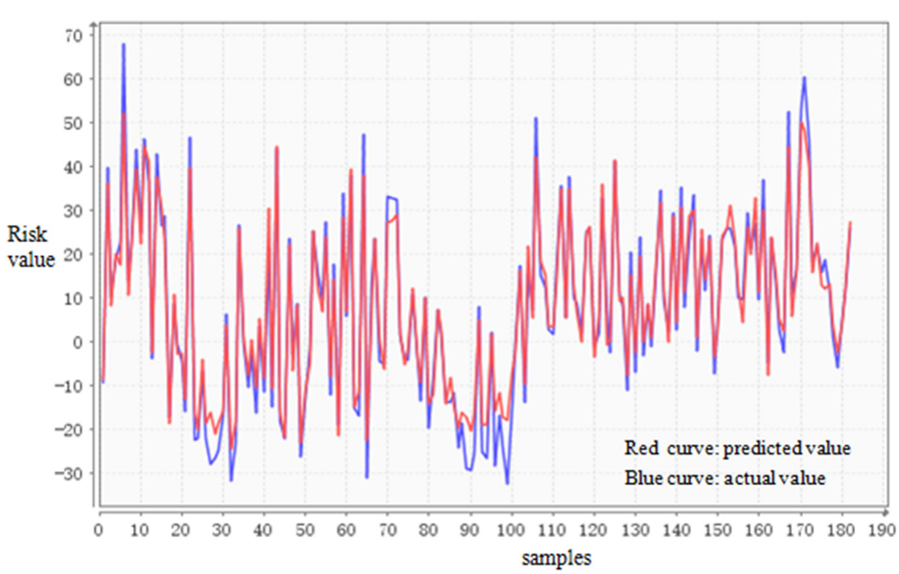

Figure 4 Predicted values vs. actual values

Table 4 Comparison between different models

Number	Actual value	Our BPNN		Traditional ANN	
		Predicted value	Relative error	Predicted value	Relative error
1	27.3507	25.0621	0.0837	24.1325	0.1177
2	-4.5204	-4.1472	0.0825	-1.623	0.641
3	4.9198	4.1877	0.1488	4.7586	0.0328
4	-2.5633	-1.6853	0.3425	-2.2418	0.1254
5	2.8825	3.2735	0.1356	2.0445	0.2907
6	9.5536	9.9616	0.0427	9.3962	0.0165
7	22.9823	21.677	0.0568	24.7462	0.0768
8	-0.1688	0.3796	3.2488	-0.6593	2.9061
9	6.1046	5.7827	0.0527	1.4603	0.7608
10	17.8784	18.4076	0.0296	12.6524	0.2923
11	-16.9062	-11.7765	0.3034	-17.4431	0.0318
12	-6.1492	-4.5624	0.258	-8.1258	0.3214
13	33.9974	27.819	0.1817	35.3916	0.041
14	-1.8067	-0.6403	0.6456	3.3625	2.8611
15	-1.526	-1.76	0.1533	4.177	3.7372
Toal			5.7657		12.2526

accuracy. Figure 4 further compares the predicted values with the actual values.

As shown in Figure 4, the predicted curve was basically consistent with the actual curve, except for a few abnormal samples. The prediction accuracy was close to the target value. This means our BPNN has been well trained.

6.3. Model simulation

To test its utility, the proposed BPNN model was compared with the traditional ANN model on the remaining 15 test samples. The comparison results are recorded in Table 4.

As shown in Table 4, our BPNN model achieved smaller relative errors in the simulation than the traditional model, and outperformed the latter in both convergence speed and model accuracy. In other words, the BPNN coupled with PCA converges to the optimal solution more efficiently than the traditional model, because the PCA reduces the impact of the coupling between original indices on prediction accuracy, making the prediction more scientific and reliable.

7. Conclusions

The digital transformation of China's manufacturing is a new phenomenon, with no experience to learn from. Many traditional manufacturing companies in China are faced with great difficulties in quickly completing the digital transformation, partly owing to the numerous uncertainties and risks that arise in the course of the transformation. For the smooth implementation of digital transformation among manufacturing companies in China, this paper identifies the risk factors of traditional manufacturing companies in digital transformation, referring to the relevant literature, and compiles them into an evaluation index system. Next, the PCA was carried out to extract the principal risk factors of digital transformation based on the survey data, and used to train and improve the BPNN risk prediction model. Simulation results show that the proposed BPNN prediction model is very useful. The risk composition is reasonable. Among the three key principal components, the weak strategy consistency is the most significant factor. This factor not only undermines the stability of the digital SC, but also affects the operating environment and weakens the risk management ability of companies. The follow-up research will further improve our prediction model. For example, the size, diversity, and quality of samples will be increased; the evaluation index system will be verified through even more tests, and adjusted to enhance its applicability to real-world scenarios.

Declaration of Competing Interest:

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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