Journal of Organizational and End User Computing
Volume 35 • Issue 3

The Optimization of Supply Chain Financing for Bank Green Credit Using Stackelberg Game Theory in Digital Economy Under Internet of Things

Hui Zhang, Pai Chai University, South Korea
Fengrui Zhang, Sichuan Agricultural University, China
Bing Gong, Tsinghua University, China
Xuan Zhang, Monroe College, USA
Yifan Zhu, The University of Queensland, Australia*

ABSTRACT

The aim is to improve small and medium-sized enterprises (SMEs)' core competitiveness and financing attainability using deep learning (DL) under economic globalization. Accordingly, this work constructs a supply chain symbiosis system based on DL, economics, and Stackelberg game theory following a status quo analysis of the financing status of SMEs. Afterward, a structural framework of supply chain financing (SCF) is designed. Further, it verifies the effectiveness of the proposed back propagation neural network (BPNN) credit evaluation model through specific enterprise data. The results show that the proposed internet of things (IoT)-based SCF SMEs-oriented BPNN credit evaluation model reaches a prediction accuracy of 91.4%. It effectively eliminates information asymmetry between banks and various capitals. As a result, banks can guarantee operation funds for the supply chain SMEs and help them minimize project risks by lowering financing leverage and through information transparency.

KEYWORDS

Credit Evaluation, Internet of Things, SME Financing, Stackelberg Game Theory, Supply Chain Symbiosis System

INTRODUCTION

By the end of the 20th century, market globalization and financial liberalization have become inevitable. The contradiction between the cost reduction of global core enterprises and the rising price of raw materials and human resources has become ever more severe. As a result, core enterprises with high market standing adopt credit sales mode and collection before delivery mode to reduce cash flow pressure and strengthen market competitiveness. In the credit sales mode, core enterprises pay after small- and medium-sized enterprises (SMEs) have provided raw materials. In the collection before delivery mode, core enterprises collect advanced payment from SMEs before delivering goods. However, both sales modes impose great finances on SMEs (Косимова, 2020; Ustyuzhanina et al., 2019). Commercial banks use supply chain financing (SCF) to optimize the traditional point-to-point

DOI: 10.4018/JOEUC.318474 *Corresponding Author

service for supply chain core enterprises. In particular, SCF can connect the core enterprises with the upstream and downstream supply chain SMEs by linking the raw material supply, semi-finished product production, and user-end commodity delivery services. Thus, SCF forms a risk-sharing community by connecting the supply chain participants, suppliers, manufacturers, distributors, retailers, and end-users.

Meanwhile, SCF adopts a new whole supply chain-oriented credit evaluation mechanism over the original single enterprise-oriented credit evaluation mechanism. Because of the new credit evaluation mechanism, financial institutions can implement better financial services for multiple subjects in the supply chain. In simpler terms, the endorsement or guarantee by core enterprises in SCF helps weaken the qualification weight of SMEs in the credit review, effectively improving SMEs' attainability of credit loans (Chen, 2019; Swanson, 2018; Raimo et al., 2021).

So far, foreign studies on SCF are relatively limited. This work summarizes them as the whole supply chain-oriented study, the SCF financing scheme-oriented analysis, SCF technical support-oriented research, and SCF third-party logistics-oriented exploration. Domestic researchers have investigated SCF mainly from the financing mode, financing risk, and financing credit risk perspectives. Thereby, both domestic and international researchers have made efforts from the theory and application of SCF. However, no universal SCF SMEs-oriented credit risk evaluation index system (EIS) is acknowledged in the academic circle (He et al., 2019; Wang et al., 2017). Thus, the index selection is mostly very subjective. In the past, quantitative indexes were chosen to evaluate SCF's credit risk. In practice, scholars prefer fuzzy qualitative indexes to assess credit risk. Principal component analysis (PCA) or regression analysis can somehow trade off the impact of subjective evaluation. Nevertheless, they require a large-scale training set, which is difficult to operate (Song et al., 2020; Fu & Zhu, 2019).

According to the idea of SCF, this work attempts to transfer the bank's focus from assessing the SMEs' credit to evaluating the entire supply chain, from considering static indexes, such as financial data of SMEs, to considering dynamic transaction facts. This enables banks to grasp the essence behind the SMEs' credit risks to deal with various threats, develop SCF services, and help SCF enterprises solve financing difficulties. Following an in-depth study and understanding of back propagation neural network (BPNN) characteristics and the advantages of BPNN-based credit risk evaluation for SCF enterprises, this work proposes the SCF SMEs-oriented credit risk evaluation model. It tries to minimize the influence of human factors and fuzzy randomness and ensures the objectivity and accuracy of the evaluation results. Moreover, BPNN has strong dynamics. With the increase of samples and the advance of time, it can further learn and track financial data dynamically.

According to the research on domestic and foreign theories and literature related to green SCF, this work draws on relevant green SCF models and the current status of China's implementation and development of green SCF to clarify research issues. Then, based on the investigation of SMEs that cause environmental pollution in the process of SCF, combined with evolutionary game theory, an evolutionary game model is implemented between core enterprises and their upstream SMEs during the green SCF process. Using this model analysis, it is concluded that the core enterprises in the green SCF can promote their upstream SMEs to adopt environmental management strategies in the production process by optimizing the guaranteed system. Numerical simulation analysis demonstrates that implementing the green SCF strategy can solve the environmental pollution problems that frequently occur in traditional SCF, which is of positive significance for promoting green SCF practices in China. On this basis, combined with the cooperative game theory and international green SCF models, a cooperative non-cooperative game model of commercial banks and core enterprises in green SCF is constructed. Analyzing the individual and overall benefits of the two in cooperation and non-cooperation shows the necessity of collaboration between commercial banks and core enterprises further to promote the implementation of the green SCF strategy and also points out the way forward for further development of green SCF in China (Zhang et al., 2022; Feng et al., 2021).

LITERATURE REVIEW

The green credit-based SCF has its origin in practical economic-financial activities. Commercial banks launch green credit-based SCF services as a more sustainable business model to strengthen customer trust and enhance corporate social responsibility (CSR). For example, SMEs in the upstream supply chain of developing countries can be encouraged to solve the problem of environmental pollution and provide financing services to SMEs (Lei et al., 2022).

There is plenty of research on the credit financing dilemma of SMEs and its causes. Turvey (2017) pointed out the financing obstacles of SMEs from several aspects: a lack of a social financing support system, an inappropriate credit service system, and a poor enterprise reputation. Lee et al. (2018) analyzed the causes of SMEs' financing difficulties: SMEs produced terminal products in the seller's market rather than intermediate products and services. Their economic benefits could not be guaranteed under the increasing competition in the buyer's market. Xu and Gui (2019) suggested that the financial gap was caused by excessive demand and insufficient fund supply under financial repression in the current market conditions.

The information asymmetry between banks and enterprises exacerbated the gap. Yang et al. (2019) believed that non-standard financing, the influence of the ownership concept, and the difficulty of mortgage guarantee were constraints of SME financing. Alonso and Carbó (2020) proposed that banks naturally favored large enterprises in providing credit support while ignoring SMEs with backward production equipment and limited financial and material resources. This caused SMEs credit difficulties.

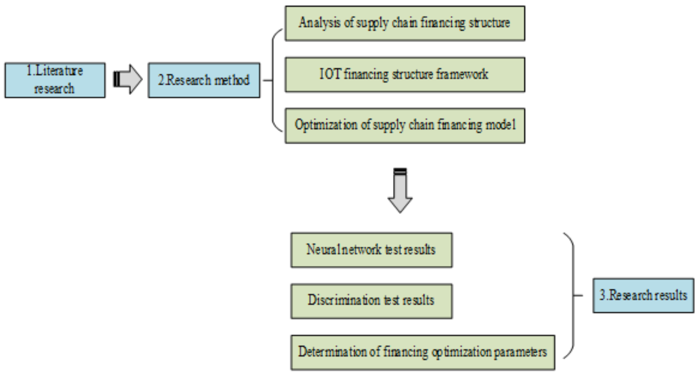
Meanwhile, aiming at the problem of financing difficulty of SMEs, there are many studies on the countermeasure level. Sun et al. (2021) claimed that the SMEs' financing difficulties were closely related to China's banking industry structure. Banking institutions lacked information on customer risk management, and a few major large banks mastered excessive financial resources and market share. Thus, there was a need to vigorously develop small and medium-sized financial institutions to support SME financing. Liu et al. (2020) contended that the SMEs' credit financing difficulties involved some systematic problems. They repositioned SME financing from the system theory by improving various elements and coordination in the system to provide substantive impetus to SME financing (Wang & Dai, 2022) (Liu et al., 2021).

Most existing literature studies SCF-related problems from a qualitative perspective. The few quantitative studies can provide a reference basis for this work. Meanwhile, most literature only considers the role of the main stakeholders in green credit-based SCF implementation. The impact of the interaction of two or even more stakeholders is not mined in-depth on the implementation and development of green credit-based SCF. Therefore, studying the game relationship between relevant stakeholders in green credit-based SCF is particularly important. This work analyzes the survival and symbiotic mechanism of the supply chain's large, medium, and small enterprises.

Consequently, it proposes an SCF structural framework based on the Internet of Things (IoT) and using Stackelberg game theory and combining qualitative and quantitative research methods. It factors in the two aspects of SCF: decision-making benefits and financing models. The proposed framework optimizes the risks and benefits of existing enterprise management, operation, and decision-making. Furthermore, it determines the critical role of the credit-based supply chain in reducing transaction costs and financing risks. Figure 1 shows the specific framework.

Based on the research framework listed in Figure 1, the first section presents the questions to be explored. After determining the research content and methods used, a technical roadmap for the research is given. The next section summarizes the relevant domestic and international literature and provides a theoretical basis for the smooth development of the study. The following section introduces the relevant theories and methods and implements an evolutionary game model with the core enterprise's guarantee behavior as the core. The remaining sections analyze the performance of the evolutionary game model, provide pertinent suggestions for promoting the implementation and development of green SCF in China based on the conclusions obtained above, and, finally, summarize the work of the full text and propose future research directions.

Figure 1. Research framework



METHODOLOGY

Analysis of SCF Structure in the IoT

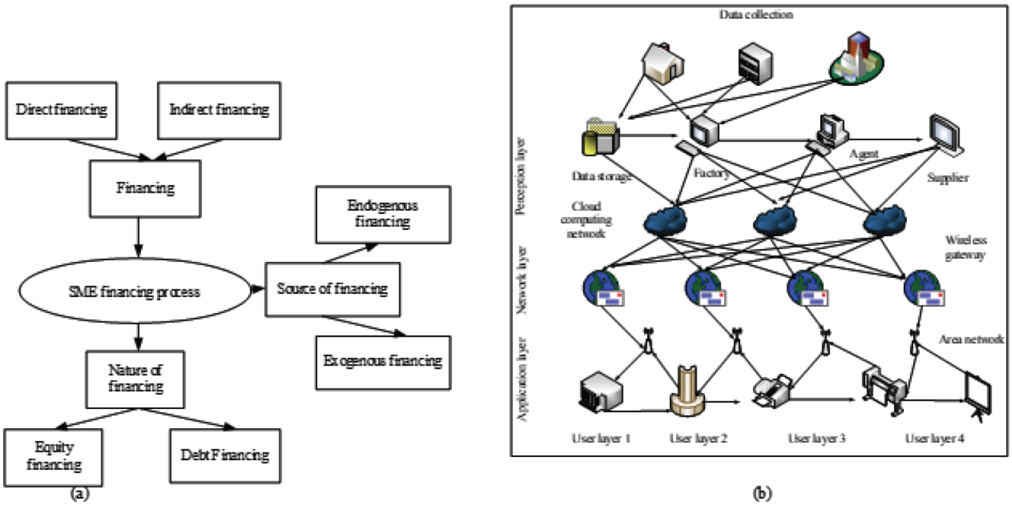
From the perspective of banking business expansion, SCF refers to a financing pattern in which banks evaluate the whole supply chain through the core enterprises' credit and supply chain management (SCM). Based on this, banks provide financial products to core enterprises in the strong link and upstream and downstream enterprises in weak ties. From the perspective of financing function, SCF is a new financing pattern integrating capital flow, information flow, and logistics, providing financial products and services for the monetary fund operation of the whole supply chain (especially SMEs). Thereby it improves the supply chain fund operation efficiency. From the functional perspective of financing scope, SCF integrates capital flow in SCM to provide credit financing for supply chain enterprises in weak links. Thus, SCF can provide financial products and services for these enterprises in all links (Heydari et al., 2017; Feng & Chen, 2022).

Essentially, SCF is a financial service of commercial banks based on the internal supply chain transaction structure. SCF uses a self-compensating trade financing model. It factors in logistics enterprises, core enterprises, and capital flow guidance tools as risk control variables. Meanwhile, SCF provides enterprises with credit extension, settlement, and financial services. For example, SCF can facilitate upstream raw material purchase and downstream goods delivery (Chen et al., 2017). This work combines the traditional financing structure with a neural network (NN) to improve the detection efficiency of the SCF structural model. Most current studies are limited to the qualitative analysis of financial or SCF enterprises' concept, mode, and respective income risk. There are also a few quantitative works on price strategy, order quantity optimization, and credit risk control. However, quantitative and qualitative studies only explore the performance and interests of core enterprises in the supply chain (Zhang et al., 2021).

Moreover, mathematical models and theoretical innovations mostly prove the existing literature. No dynamic models have been applied to consider the coordination of logistics, information flow, and capital flow in the supply chain. This work will combine quantitative and qualitative analysis using the Stackelberg game theory on the IoT platform concerning these problems. The IoT can connect any object to the Internet for information exchange and communication. IoT involves Radio Frequency Identification (RFID) technology, infrared sensor, Global Positioning System (GPS), laser scanner, and gas sensor and realizes intelligent identification, positioning, tracking, monitoring, and management according to the agreed protocol (Tian et al., 2019). The specific structure is displayed in Figure 2.

The Stackelberg game is a two-stage complete information dynamic game, and the time of the game is sequential. The main idea is that both parties choose their strategies according to the other's

Figure 2. Financing structure mode



Note. *Panel a shows the financing structure of SMEs; panel b shows the IoT financing structure.*

possible strategic decisions to maximize their interests until the Nash equilibrium is obtained (Liu et al., 2018). In the Stackelberg game model, the first decision-maker is called the leader. The remaining players, namely followers, make decisions according to the leader's decision. Then, the leader re-adjusts his decision according to the followers' decision until the Nash equilibrium is reached. This work proposes the IoT financing structural model: banks make financing decisions with the loan interest rate (r) as the decision variable. Suppliers and dealers make operation decisions with order batch (Q) and wholesale price (W) as the decision variables.

Optimization of SCF Model

In the era of IoT, the Internet+ structure is flooded with every industry, generating massive amounts of data. Hence, efficient data processing has become one of the leading research topics. This work processes complex financial data by implementing the financing model using the BPNN, which is a multilayer feedforward neural network (FNN) with the characteristics of error backward transmission and signals onward transmission (Luo et al., 2018; Harish et al., 2021). The signals go from the input layer to the hidden layer and the output layer during forwarding transmission and are outputted. The BPNN can automatically extract the "reasonable rules" regarding data, learning to adjust network weights. Therefore, the BPNN is introduced and optimized to evaluate the supply chain process (Liu et al., 2019; Kaupadien et al., 2019). Specifically, the sample data or evaluation indexes are input into the BPNN algorithm, and the output is calculated:

$$y_i = 1 / \left[1 + exp\left(-\sum_{i=1}^{n} w_{ij} x_i \right) \right] \tag{1}$$

In Equation 1, the number of input nodes of node j is n; y_i refers to the output value of the input node; and ω_{ij} denotes the weight between the ith node and the jth node. When $i = 0$, ω_{ij} represents the threshold, and $x_i = 1$. Then, the expected output and the calculated output are compared, and the node threshold and weight of layer k are modified:

$$\omega_{ij}\left(k+1\right)=\omega_{ij}\left(k\right)+\eta\sigma_{j}x_{i}+\alpha\left[\omega_{ij}\left(k\right)-\omega_{ij}\left(k-1\right)\right] \tag{2}$$

In Equation 2, ω_{ij} stands for the threshold (the connection weight) of the *i*th node and the *j*th node in layer *k−1*; *xi* denotes the output value of the input node; η indicates the learning rate (LR; 0 < η < 1); and α stands for the impulse coefficient (0 < α < 1). The value of σ_j is related to the bias. Equation 3 can calculate output nodes:

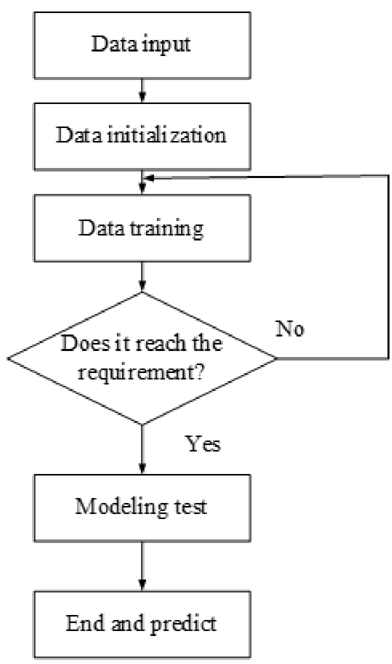
$$\sigma_{j}=y_{i}\left(1-y_{i}\right)\left(d_{j}-y_{i}\right) \tag{3}$$

The variables y_i and d_j denote the actual output and the expected result of the *j*th node, respectively. The outcome of the hidden layer node should be calculated backwards because its outcome cannot be compared:

$$\sigma_{j}=x_{i}\left(1-x_{j}\right)\sum_{j=0}^{m}\sigma_{j}\omega_{ij} \tag{4}$$

In Equation 4, x_i means the actual output of node *i*; *m* represents the number of output nodes. The algorithm is iterative, every iteration means a learning cycle, and the value of ω will be adjusted at every learning cycle. In this way, the network is trained repeatedly, and results are output. The iteration does not stop until the error between the calculated and expected production is less than a given value. The learning and training process ends when the iteration stops, and the evaluation model is determined. The specific method is given in Figure 3.

Figure 3. Optimization flowchart of the BPNN-based financing model



Data Source

SCF mainly serves SMEs. In China, the data disclosure system of SMEs is underdeveloped, and data collection is complex. Here, the sample enterprise data are chosen from the SME database of a commercial bank. Samples are selected based on three standards to obtain as much sample data as possible (Qamruzzaman & Jianguo, 2019): (1) SMEs in the petrochemical, automobile, and steel industries are selected, where SCF services have matured; (2) the scale of sampled enterprises should conform to the standard of SMEs in China; and (3) enterprise data should be comprehensive and reliable. Here, the information on upstream and downstream SMEs' core enterprises is searched through websites such as Enterprise Investigation and Sky-Eye Investigation. Then, the corresponding qualitative information and financial data are acquired based on the results and the Shanghai Stock Exchange (SSE), Shenzhen Stock Exchange (SHZ), and Tonghuashun Website. Finally, 150 pieces of qualified enterprise data were selected (Lin et al., 2020).

Data Normalization Processing

Enterprises without a non-performing loan (NPL) are defined as $Y = O$. Enterprises with NPLs are defined as $Y = l$. Furthermore, five indexes are selected: the macro-economy, the characteristics of SMEs, core enterprises, the overall supply chain situation, and the actual situation of financing projects. Measurement standards for indexes are inconsistent, and the sample data do not have a uniform commonality. Therefore, the original data should be normalized to control all indexes within [0,1]. For some indexes, the greater their values are, the better the enterprise benefit is, as expressed in Equations 5–7:

$$y = \left(y_{\max} - y_{\min}\right) * \frac{\left(x_{ij} - x_{i\min}\right)}{\left(x_{i\max} - x_{i\min}\right)} + y_{\min} \tag{5}$$

The values $y_{max} = 1$ and $y_{min} = 0$ are introduced into Equation 5 to obtain Equation 6:

$$y = \left(x_{ij} - x_{i\min}\right) / \left(x_{i\max} - x_{i\min}\right) \tag{6}$$

For other indexes, the smaller their values are, the better the enterprise benefit is, which is calculated by Equation 7:

$$y = \left(x_{i\max} - x_{ij}\right) / \left(x_{i\max} - x_{i\min}\right) \tag{7}$$

Variables x_{imax} and x_{imin} demonstrate the maximum and minimum index values; x_{ij} refers to the j piece of data in the ith index. Here,150 pieces of enterprise sample data are divided into a training set and test set, each containing 80 and 70 samples, respectively, through the random sampling method without playback. The BPNN with two classification modes containing 28 input neurons and ten hidden layer nodes is realized by Matlab (Nord et al., 2019; Jia et al., 2018).

Performance Analysis

First, the discrimination of the BPNN credit evaluation model is tested under the original 150 pieces of sample data. At the same time, the bootstrap method is used to train and expand the BPNN credit evaluation model on richer sample data. The obtained results are compared with the original sample data. The given LR is ε = 0.05, the number of iterations is 2,000, and the target is 0.00001. The excitation function of the hidden layer is set as *logsig*, the excitation function of the output layer is formed as *purelin*, and the training function is set as *traingdx*.

One hundred fifty pieces of data are divided into 80 and 70 parts of training and test samples, respectively. Seventy pieces of test samples are introduced into the trained BPNN credit evaluation model to obtain 70 reports of output. Next, the results are sorted from large to small. Enterprises with and without NPLs are counted in each interval. The experimental environment is configured with an i7 central processing unit (CPU), 64-bit Windows 7 operating system, 16 GB random access memory (RAM), and MATLAB 2016b for programming (Barra et al., 2020; Zhang, 2019; Tsai & Peng, 2017; Giri & Sarker,2017; Dar et al., 2017).

ANALYSIS OF EMPIRICAL RESULTS

BPNN Test Results Before and After Optimization

Without putting back, the random sampling method is used to divide 150 groups of enterprise sample data into 80 training samples and 70 groups of testing samples. Then, Matlab realizes a binary classification pattern BPNN with 28 input neurons and ten middle layer nodes. Afterward, 80 groups of training samples are used to train the BPNN until the model converges within 124 training steps. The mean square error (MSE) is only 0.000951, and the network performance measured by the *msereg* function is 0.0381. Figure 4 demonstrates the results of the model training.

Figure 4 illustrates that the model output and absolute error are stable as the number of training samples changes. For example, the MSE is only 0.000951, and the production of the BPNN model optimized by the *msereg* function is 0.0381. The prediction accuracy is 96%. This shows that the optimized BPNN model has been well-trained on the training data set. Its performance has been significantly improved. Now, the trained BPNN is verified on the test set.

Figures 4c and 4d reveal that 6 of the 70 pieces of samples have been misjudged. Thus, the prediction accuracy of the BPNN model is 90.6%. Notably, the prediction accuracy of the BPNN model for enterprises with NPLs has reached 100%. Therefore, the proposed BPNN model can better process relevant data to pick enterprises without NPLs (Wu & Zhang, 2022).

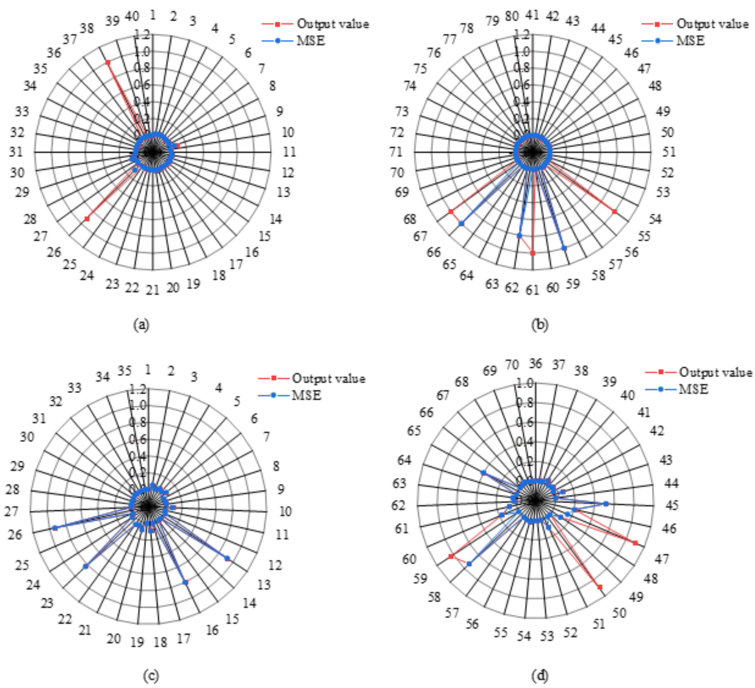
Discrimination Test Results

Discrimination is an important index to measure the prediction ability of the credit evaluation model. Firstly, this work tests the discrimination of the BPNN credit evaluation model under the original 150 groups of sample data. At the same time, the bootstrap method is used to train and expand the discrimination of the BPNN credit evaluation model on more extensive sample data. Secondly, the results are compared with the original sample data to obtain the final discrimination test results.

Figure 5 outlines the discrimination test result and receiver operating characteristic (ROC) curve before and after data normalization. Figures 5a and b calculate the final area under ROC (AUC) to be 0.9251. The BPNN credit evaluation model has high discriminability for evaluating the credit of SMEs in SCF, and its prediction accuracy is high. However, when the threshold is set higher than 0.9, a cliff appears in the curve, and the model's prediction ability for enterprises with NLPs is almost zero. Presumably, there are insufficient sample enterprises with NLPs in the training set and only one in the test set. Therefore, the sample size must be expanded to obtain more accurate discrimination. A new sample dataset containing 150 groups is obtained using the bootstrap method for sampling with playback repeated 150 times. Then, all new data sets are integrated into sample data sets with a sample capacity of 750, containing 145 enterprises with NLPs.

Further, 750 groups of data are randomly divided into 400 training samples and 350 testing samples. The training and test sets contain 85 and 60 enterprises with NLPs, respectively. Next, 240 results obtained on the test set are sorted according to size. Enterprises with and without NLPs in each interval are counted. Figures 5c and 5d corroborate that the improved BPNN credit evaluation model has high discrimination for SCF SMEs, and its prediction accuracy is high. The ROC indicates that the model performance has been significantly improved after increased data samples.

Figure 4. Test results



Note. Panel a shows the training result of BPNN before optimization; panel b shows the training result of BPNN after optimization; panel c shows the test result of BPNN before optimization; and panel d shows the test result of BPNN after optimization.

Determination of Financing Optimization Parameters

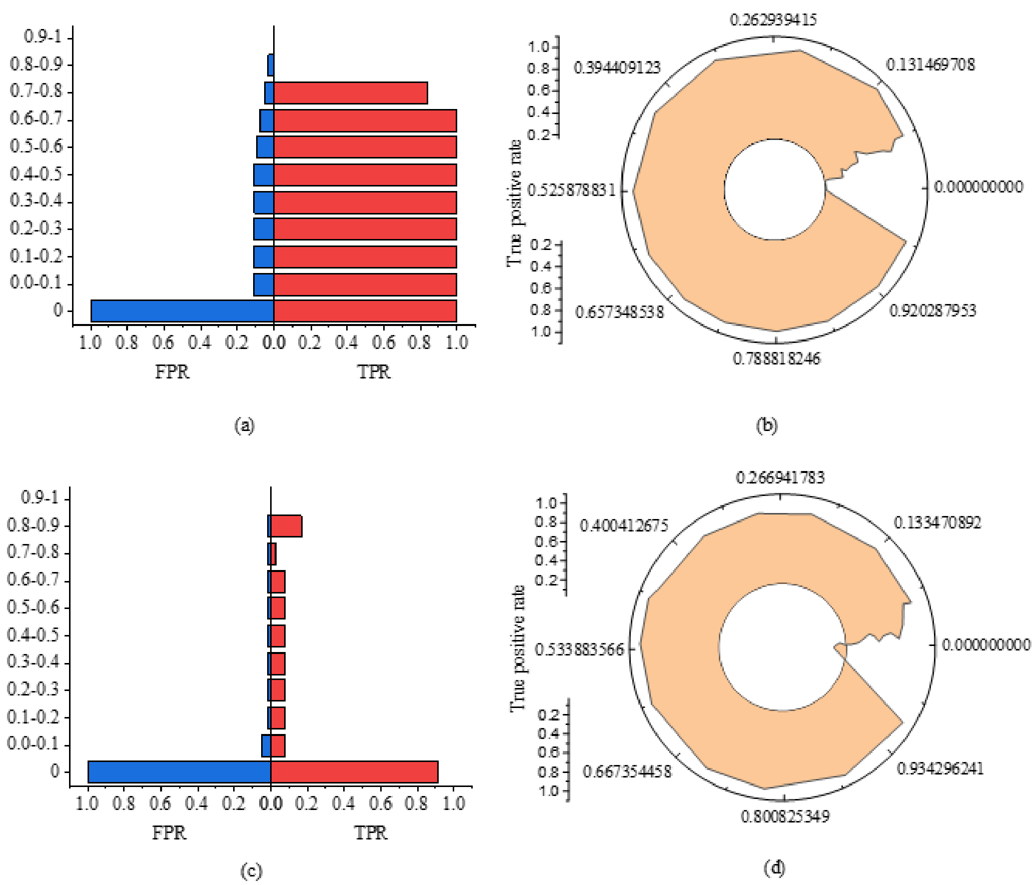
Figure 6 counts the error of the proposed optimized BPNN credit evaluation model. Figure 6a compares the model error under a different number of hidden layers. The hidden layers selected are 10, 11, 12, 13, 14, and 15, respectively. The model's error decreases with the number of iterations. The model error converges the fastest when the number of hidden layers is 12, reaching as low as 0.49, which meets the error requirements of the system. Therefore, the number of hidden layers is finally selected as 12.

Figures 6b and 6c display the model error under LR = 0.03 and 0.004, respectively. The LR also dramatically impacts the convergence and stability of the BPNN. For example, when the LR = 0.03 and 0.004, the model error is significantly reduced to 0.00000996 and 0.00000999, respectively. The error is more minor when LR = 0.03. Although the error under an LR = 0.004 and LR = 0.03 is much close, the error fluctuation is more severe when LR = 0.004. Through comprehensive analysis, the LR of the proposed BPNN credit evaluation model is 0.03.

Empirical Analysis of Different SCF SMEs-Oriented Credit Evaluation Models

Figure 7 compares the results of the performance of different models. It suggests that with an increase in sample enterprise data, the performance of different evaluation models varies greatly. In particular, the proposed BPNN credit evaluation model's total misjudgment rate and accuracy are 8.6% and 91.4% on the test set. The proposed BPNN credit evaluation model has the highest accuracy on the training set, with an average prediction accuracy of more than 95%. The CNN model follows right behind, with an average prediction accuracy of more than 93%. The prediction results on the test set and the training set are consistent. However, the prediction accuracy of the analytical hierarchy process

Figure 5. Results of the discrimination test and ROC curve



Note. Panel a shows discrimination test results; panel b shows ROC curve results; panel c shows the results of the discrimination test after normalization; and panel d shows the normalized ROC curve results.

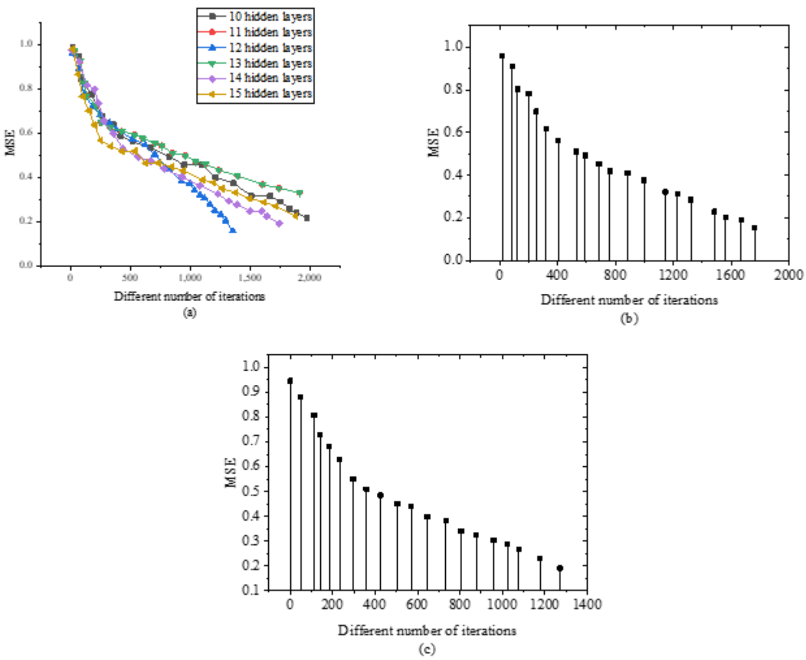
(AHP) model is relatively low, only about 75%. In addition, the misjudgment rate of the proposed BPNN credit evaluation model stays below 2.5% on the training set and about 10% on the test set, still very competitive over other network structures. The comparative analysis with other evaluation models suggests that the proposed BPNN credit evaluation model shows good prediction results in accuracy and misjudgment rate. Thus, the proposed SCF SMEs-oriented BPNN credit evaluation model has high predictability and overcomes the information asymmetry between banks and capitals.

DISCUSSION

Significance of Theory

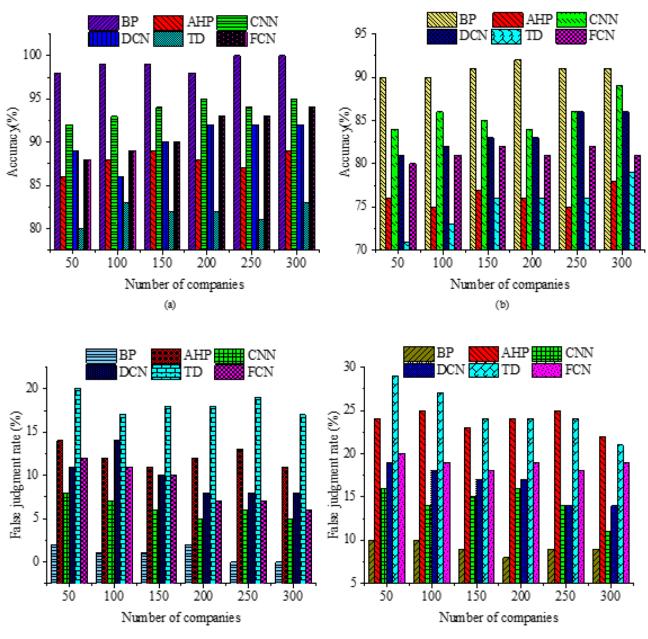
Currently, the domestic theoretical research related to SCF mainly focuses on risk management and credit risk evaluation. On the one hand, supply chain risk management (SCRM) primarily uses the qualitative analysis method to discuss the classification and characteristics of risk comprehensively. There are few studies combining the quantitative analysis method and quantitative model to evaluate credit risks objectively. On the other hand, the SCF-oriented credit risk evaluation mainly considers the

Figure 6. Statistics of the proposed BPNN credit evaluation model error



Note. Panel a shows model errors; in panel b, LR = 0.03; and in panel c, LR = 0.04.

Figure 7. Performance analysis results of different models



Note. Panel a shows accuracy on the training set; panel b shows accuracy on the test set; panel c shows misjudgment on the training set; and panel d shows misjudgment on the test set.

default risk of single enterprises. This work ignores the importance and status of financing enterprises concerning the whole supply chain and the transaction histories of core enterprises. Instead, from the perspective of banks and other financial institutions, it suggests controlling and evaluating SCF enterprises' credit risk based on the supply chain's overall characteristics.

In short, the traditional SCF risks are summarized systematically according to the financing stage based on the SCF risk management, the SCF enterprises' characteristics, risk evaluation, and IoT-based financial theory. China's SCF has been developing toward Internetization in an all-around way, and IoT-based financing is still in its infancy. Thus, the research on traditional and emerging risks is of great value. The proposed BPNN credit evaluation model's total misjudgment rate and accuracy on the test group are 8.6% and 91.4%. Compared with the latest model, it has apparent accuracy and misjudgment rate advantages. This work lays a foundation for subsequent risk assessment, information security simulation, and IoT-based financing platform construction. It provides a new theoretical research method for banks to evaluate SME credit risks.

Significance of Practice

Based on the idea of SCF, this paper shifts the focus of banks from SME credit evaluations to the whole supply chain evaluation, and from the static indexes, such as SME financial data, to the dynamic transaction facts. It helps banks grasp the essence behind SME credit risks. It is conducive for banks to deal with various risks, carry out SCF services, and help SCF enterprises solve financing difficulties.

Based on the previous studies, this work puts forward the SCF structural framework, but there are still many deficiencies. Firstly, the proposed model is based on a single financing cycle with a single supply chain goal. Accordingly, the follow-up work will consider the financing decision-making behavior of cooperative supply chain enterprises from multi-objectives and multi-cycles. Secondly, the structure, process, and benefits of various services of SCF have been introduced and analyzed from the perspective of enterprises. There are few discussions and evaluations on the financial innovation of SCF from the perspective of industry or government. The future work will conduct in-depth research in these two directions and constantly improve the research model.

CONCLUSION

In order to improve the core competitiveness of SMEs, this work constructs a supply chain symbiosis system based on deep learning, economics, and game theory following a status quo analysis of the financing situation of SMEs. It designs an SCF structural framework and further verifies the effectiveness of the proposed BPNN credit evaluation model using specific enterprise data. The results show that with the increasing number of sample enterprises, the performance of all control models and the proposed model fluctuates. The proposed BPNN credit evaluation model's total misjudgment rate and accuracy on the test set are 8.6% and 91.4%. Compared with the latest model, it has obvious accuracy and misjudgment rate advantages. Lastly, some research deficiencies are observed: the accuracy of the proposed SCF SME-oriented BPNN credit evaluation model is greatly affected by the number and quality of training samples. With more enterprises joining the SCF, the proposed BPNN credit evaluation model can gradually improve its accuracy using sufficient samples. Meanwhile, every application will take some time before its mature industrial application, and so is the bank's SCF business. Besides this, commercial banks' evaluations of supply chain enterprise credit risks depend on personal experience, professional skills, sample number, and sample distribution. This results in fuzzy decision-making. To this end, the proposed BPNN credit evaluation model needs further improvement. On top of SMEs, other enterprise entities can be considered in the follow-up research. The qualitative credit risk evaluation indexes can be further refined and simplified.

DATA AVAILABILITY STATEMENT

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

FUNDING STATEMENT

This research received no external funding.

ACKNOWLEDGMENT

The authors acknowledge the help from the university colleagues.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of Interest

All authors declare no conflicts of interest.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any authors. Informed consent was obtained from all individual participants included in the study.

REFERENCES

Косимова, М. А. (2020). Improvement of the strategy of vertical integration in industrial enterprises. *Архив научных исследований, 13*, 214–223.

Alonso, A., & Carbó, J. M. (2020). Machine learning in credit risk: Measuring the dilemma between prediction and supervisory cost. *Documentos de Trabajo/Banco de España, 12*(3), 2032–2041.

Barra, S., Carta, S. M., Corrigan, A., Podda A.S., Recupero D.R.. (2020). Deep learning and time series-to-image encoding for financial forecasting. *IEEE/CAA Journal of Automatica Sinica, 7*(3), 683–692.

Chen, C. J. (2019). Developing a model for supply chain agility and innovativeness to enhance firms' competitive advantage. *Management Decision*, *13*(3), 124–131. doi:10.1108/MD-12-2017-1236

Chen, Z., Li, Y., Wu, Y., Wu, Y., & Luo, J. (2017). The transition from traditional banking to mobile internet finance: An organizational innovation perspective-a comparative study of Citibank and ICBC. *Financial Innovation*, *3*(1), 1–16. doi:10.1186/s40854-017-0062-0

Dar, M. S., Ahmed, S., & Raziq, A. (2017). Small and medium-sized enterprises in Pakistan: Definition and critical issues. *Pakistan Business Review*, *19*(1), 46–70.

Feng, B., Sun, K., Zhong, Z., & Chen, M. (2021). The internal connection analysis of information sharing and investment performance in the venture capital network community. *International Journal of Environmental Research and Public Health*, *18*(22), 11943. doi:10.3390/ijerph182211943 PMID:34831699

Feng, Z., & Chen, M. (2022). Platformance-based cross-border import retail e-commerce service quality evaluation using an artificial neural network analysis. *Journal of Global Information Management*, *30*(11), 1–17. Advance online publication. doi:10.4018/JGIM.306271

Fu, Y., & Zhu, J. (2019). Big production enterprise supply chain endogenous risk management based on blockchain. *IEEE Access: Practical Innovations, Open Solutions*, *153*, 10–19. doi:10.1109/ACCESS.2019.2895327

Giri, B., & Sarker, B. R. (2017). Improving performance by coordinating a supply chain with third-party logistics outsourcing under production disruption. *Computers & Industrial Engineering*, *142*(1), 103168–103177. doi:10.1016/j.cie.2016.11.022

Harish, A. R., Liu, X. L., Zhong, R. Y., & Huang, G. (2021). Log-flock: A blockchain-enabled platform for digital asset valuation and risk assessment in e-commerce logistics financing. *Computers & Industrial Engineering*, *151*, 107001–107012. doi:10.1016/j.cie.2020.107001

He, L., Zhang, L., Zhong, Z., & Feng, W. (2019). Green credit, renewable energy investment, and green economy development: Empirical analysis based on 150 listed companies of China. *Journal of Cleaner Production*, *208*, 363–372. doi:10.1016/j.jclepro.2018.10.119

Heydari, J., Choi, T. M., & Radkhah, S. (2017). Pareto improving supply chain coordination under a money-back guarantee service program. *Service Science*, *9*(2), 91–105. doi:10.1287/serv.2016.0153

Jia, L., Xu, Y., Sun, Y., Feng, S., & Anapalagan, A. (2018). Stackelberg game approaches for anti-jamming defense in wireless networks. *IEEE Wireless Communications*, *25*(6), 120–128. doi:10.1109/MWC.2017.1700363

Kaupadien, L., Ramanauskait, S., & Enys, A. (2019). Information security management framework suitability estimation for small and medium enterprise. *Technological and Economic Development of Economy*, *25*(5), 979–997. doi:10.3846/tede.2019.10298

Lee, H. H., Zhou, J., & Wang, J. (2018). Trade credit financing under competition and its impact on firm performance in supply chains. *Manufacturing & Service Operations Management*, *20*(1), 36–52. doi:10.1287/msom.2017.0640

Lei, Z., Gong, G., Wang, T., & Li, W. (2022). Accounting information quality, financing constraints, and company innovation investment efficiency by big data analysis. *Journal of Organizational and End User Computing*, *34*(3), 1–21. doi:10.4018/JOEUC.292525

Lin, M. S., Song, H. J., Sharma, A., & Lee, S. (2020). Formal and informal SME financing in the restaurant industry: The impact of the macroenvironment. *Journal of Hospitality and Tourism Management*, *16*(4), 45276–45284. doi:10.1016/j.jhtm.2020.08.017

Liu, H., Pretorius, L., & Jiang, D. (2018). Optimization of cold chain logistics distribution network terminal. *EURASIP Journal on Wireless Communications and Networking*, *2018*(1), 1–9. doi:10.1186/s13638-018-1168-4

Liu, X., Peng, X., & Stuart, M. (2020). Multiparty game research and example analysis in supply chain finance system based on MPDE theory. *Alexandria Engineering Journal*, *59*(4), 2315–2321. doi:10.1016/j.aej.2020.02.023

Liu, Y., Zhang, H., Wu, Y., & Dong, Y. (2019). Ranking range based approach to MADM under incomplete context and its application in venture investment evaluation. *Technological and Economic Development of Economy*, *25*(5), 13–16. doi:10.3846/tede.2019.10296

Liu, Y., Zhang, S., Chen, M., Wu, Y., & Chen, Z. (2021). The sustainable development of financial topic detection and trend prediction by data mining. *Sustainability*, *13*(14), 7585. doi:10.3390/su13147585

Luo, S., Zhang, Y., & Zhou, G. (2018). Financial structure and financing constraints: Evidence on small- and medium-sized enterprises in China. *Sustainability*, *10*(6), 1774–1783. doi:10.3390/su10061774

Nord, J. H., Koohang, A., & Paliszkiewicz, J. (2019). The Internet of Things: Review and theoretical framework. *Expert Systems with Applications*, *3*(5), 13397–13108. doi:10.1016/j.eswa.2019.05.014

Qamruzzaman, M., & Jianguo, W. (2019). SME financing innovation and SME development in Bangladesh: An application of ARDL. *Journal of Small Business and Entrepreneurship*, *31*(6), 521–545. doi:10.1080/08276331.2018.1468975

Raimo, N., Caragnano, A., Zito, M., Vitolla, F., & Mariani, M. (2021). Extending the benefits of ESG disclosure: The effect on the cost of debt financing. *Corporate Social Responsibility and Environmental Management*, *2*(3), 114–123. doi:10.1002/csr.2134

Song, H., Yang, X., & Yu, K. (2020). How do supply chain network and SMEs' operational capabilities enhance working capital financing? An integrative signaling view. *International Journal of Production Economics*, *220*, 107447–107453. doi:10.1016/j.ijpe.2019.07.020

Sun, W., Dedahanov, A. T., Shin, H. Y., & Li, W. P. (2021). Using extended complexity theory to test SMEs' adoption of blockchain-based loan system. *PLoS One*, *16*(2), 0245964–0245973. doi:10.1371/journal.pone.0245964 PMID:33544745

Swanson, E. T. (2018). The federal reserve is not very constrained by the lower bound on nominal interest rates. *National Bureau of Economic Research, 2*(5), 2205–2213.

Tian, X., Xu, Z., & Gu, J. (2019). Group decision-making models for venture capitalists: The PROMETHEE with hesitant fuzzy linguistic information. *Technological and Economic Development of Economy*, *25*(5), 1–31. doi:10.3846/tede.2019.8741

Tsai, C. H., & Peng, K. J. (2017). The fintech revolution and financial regulation: The case of online supply-chain financing. *Asian Journal of Law and Society*, *4*(1), 4109–4113. doi:10.1017/als.2016.65

Turvey, C. G. (2017). Historical developments in agricultural finance and the genesis of America's farm credit system. *Agricultural Finance Review*, *12*(2), 147–152. doi:10.1108/AFR-09-2016-0076

Ustyuzhanina, E., Evsukov, S., Ustyuzhanin, V., & Novikova, E. (2019). The distribution of economic rent within global value chains in resource management. *International Journal of Supply Chain Management*, *8*(6), 1018–1026.

Wang, C., Wang, W., & Huang, R. (2017). Supply chain enterprise operations and government carbon tax decisions considering carbon emissions. *Journal of Cleaner Production*, *152*, 152271–152280. doi:10.1016/j.jclepro.2017.03.051

Wang, J., & Dai, Y. (2022). The agglomeration mechanism of network emerging e-commerce industry based on social science. *Journal of Organizational and End User Computing*, *34*(3), 1–16. doi:10.4018/JOEUC.291561

Wu, J., & Zhang, K. (2022). Machine learning algorithms for big data applications with policy implementation. *Journal of Organizational and End User Computing*, *34*(3), 1–13. Advance online publication. doi:10.4018/JOEUC.287570

Xu, G., & Gui, B. (2019). From financial repression to financial crisis? The case of China. *Asian-Pacific Economic Literature*, *33*(1), 48–63. doi:10.1111/apel.12249

Yang, Y., Chen, X., Gu, J., & Fujita, H. (2019). Alleviating financing constraints of SMEs through the supply chain. *Sustainability*, *11*(3), 673–684. doi:10.3390/su11030673

Zhang, H., Fan, L., Chen, M., & Qiu, C. (2022). The impact of SIPOC on process reengineering and sustainability of enterprise procurement management in e-commerce environments using deep learning. *Journal of Organizational and End User Computing*, *34*(8), 1–17. Advance online publication. doi:10.4018/JOEUC.306270

Zhang, Y. (2019). Application of improved BP neural network based on e-commerce supply chain network data in the forecast of aquatic product export volume. *Cognitive Systems Research*, *57*, 57228–57235. doi:10.1016/j.cogsys.2018.10.025