ITC 2/53

Information Technology
and Control
Vol. 53 / No. 2 / 2024
pp. 492-508
DOI 10.5755/j01.itc.53.2.35774

A Novel Risk-Perception Model Based on Blockchain for Supply Chain Finance of China Real Estate

Received 2023/12/01 | Accepted after revision 2024/04/29

HOW TO CITE: Fu, Q., Li, M., Li, W. (2024). A Novel Risk-Perception Model Based on Blockchain for Supply Chain Finance of China Real Estate. *Information Technology and Control,* 53(2), 492-508. https://doi.org/10.5755/j01.itc.53.2.35774

A Novel Risk-Perception Model Based on Blockchain for Supply Chain Finance of China Real Estate

Qiang Fu, Mingxia Li

Department of Management Science and Engineering, University of South China, Hengyang 421101, China;
phone: +86 15998275701; e-mail: qiangfu2021@usc.edu.cn

Weiqiang Li

Department of Robotics, University of South China, Hengyang 421101, China;
phone: +86 17840064426; e-mail: 894241628@qq.com

Corresponding author: qiangfu2021@usc.edu.cn

More than 220 enterprises in China's real estate industry have gone bankrupt, causing serious losses. The National Bureau of Statistics of China showed that the country's investment in property development fell by 8.5% year-on-year, while domestic lending dropped by 11.5% and the use of foreign capital fell by 43%. Upon this, the development of supply chain finance can alleviate the pressure on enterprise funds and stabilize the real estate market. However, risk in supply chain finance is the biggest obstacle to the development of supply chain finance and current researches on risk assessment of supply chain finance face problems such as imprecise classification, slow assessment speed, a small number of samples, and data that is easily tampered with. Therefore, this study integrated graph convolutional neural networks into the smart contracts of the contract layer of blockchain. This integration established a novel intelligent perception model for supply chain finance risk. Based on a consortium chain with the government and enterprises as nodes, the model was established, including risk monitoring, assessment, and categorized early warnings. In the risk assessment part, we compared the graph convolutional neural network with multilayer perceptron and support vector machine finding that the accuracy rate of the graphic convolutional neural network is 94%, which is higher than the above models. The intelligent risk-perception model proposed in this paper operates faster than expert judgment assessments used by banks. It also provides accurate risk levels and quantifies the probability of enterprises being classified as high-risk, offering technical support to regulatory authorities in controlling supply chain financial risk.

KEYWORDS: real estate, supply chain finance, blockchain, graphic convolutional neural network, smart contract, supply chain financial risk .

1. Introduction

In 2023, China's real estate industry attracted a wave of bankruptcies among real estate enterprises as several leading enterprises defaulted on their debts. For instance, Evergrande's debt reached 2.43 trillion CNY according to its 2022 financial report, while Yango Group accumulated a total debt of 274.6 billion CNY. On August 6, 2023, Yango Group was delisted from the Shenzhen Stock Exchange. The National Bureau of Statistics of China reported that the country's investment in property development fell by 8.5% year-on-year, while domestic lending dropped by 11.5% and the use of foreign capital decreased by 43%. According to the People's Court Announcement Network, as of October 15, 2023, more than 220 real estate-related enterprises in China had issued bankruptcy announcements.

The role of real estate finance becomes particularly critical to the healthy development of China's real estate industry, and risk regulation is a top priority. Real estate finance involves a variety of financial activities and services in the process of purchasing, developing, constructing, and investing in property, ensuring the availability of funds for real estate projects from planning to completion. Real Estate Supply Chain Finance (RE-SCF) is an important part of real estate finance, focusing on optimizing cash flow and financial transactions in the supply chain of real estate projects, and providing short-term financing to suppliers and contractors. Globalization has led to a more complex division of labor, resulting in a growing number of levels in the real estate supply chain and more intricate relationships between participants. At the same time, the high degree of correlation between Supply Chain Finance (SCF) information flow, cash flow, business flow, and logistics significantly facilitates the rapid propagation of SCF risk [11,22]. Consequently, the scope and impact of losses caused by SCF risk have dramatically expanded. Investments in real estate development contributed 7,517.297 billion CNY in total value added to all industries. Real estate development investments also drove the employment of more than 115 million people. The wave of real estate debt defaults has undoubtedly hampered economic development and caused mass unemployment among the population. According to the Wind database, from the beginning of 2022, the growth rate of China's real estate investment declined rapidly, and the unemployment rate of migrant workers once exceeded 6%. What's more, according to cement ren.com, China's largest database of cement professionals, more than 19 regions had already reduced the price of cement by more than CNY 100 per tonne. The bankruptcy of real estate enterprises has seriously affected the government's land transfer fees and the revenue of the financial sector. Additionally, in the upstream, construction industry accounts payable have become difficult to cash, resulting in a significant number of layoffs or closures among small and medium-sized enterprises (SMEs). Since the first half of 2023, over 1,300 construction enterprises have declared bankruptcy. Meanwhile, downstream real estate operating industries such as hotels, resorts, and retail operations have been experiencing revenue pressures, leading to salary cuts and layoffs.

To enhance capital liquidity in both the upstream and downstream sectors of the real estate industry and to accelerate the progress of projects, SCF offers a flexible and effective financing solution for real estate enterprises. This approach can optimize fund flows, reduce risks, and improve the stability and efficiency of the industry. SCF risk is the biggest obstacle to the development of supply chain finance, and the core part of risk control is risk assessment [17]. However, the current SCF risk assessment still has defects such as asymmetric information, inaccurate risk classification, and delayed risk warnings. Therefore, this study proposes a blockchain-based intelligent perception model for RE-SCF. This model enables comprehensive risk monitoring across the entire system, with risk levels further refined using a Graph Convolutional Neural Network (GCNN). This model can utilize the open and transparent nature of blockchain to achieve multi-level information flow, reducing the probability of risk arising from information silos. Furthermore, integrating blockchain with GCNN enables rapid and accurate risk levels assessment. This integration also quantifies the probability of enterprise risk, thereby providing regulatory authorities with a quantitative standard for controlling supply chain financial risks.

2. Current research on SCF Risk

2.1. Review of SCF Risk Control

The purpose of SCF risk assessment in real estate is to identify and quantify the risk status of enterprises in the supply chain of real estate projects, thereby devising management strategies to safeguard the project's stability and profitability.

In response to the real estate financial crisis, the United States, Greece, and Japan have notably adopted measures. These measures feature economic stimulation, government intervention, and financial regulatory actions. Artificial intelligence (AI) can conduct in-depth analysis of extensive historical transaction data, financial statements, and market dynamics, enabling more accurate predictions of potential risks. Consequently, AI, alongside expert assessment methods, has become a principal approach for banks and other financial institutions. Zhang et al. [25] used back propagation neural network to classify the credit risk of the automobile industry into three levels, which provides theoretical support for improving the profitability of banks. Sang [18] compared the back propagation neural network with a support vector machine (SVM) and verified that SVM is more suitable for the credit assessment of banks and other financial institutions in the case of small samples. To compensate for the defects of a single model, Zhu et al. [27] proposed a new integrated machine-learning method to construct an integrated model of random subspace-real AdaBoost to predict the credit risk of SMEs, which was applied to analysis and prediction of multisource data. Under the framework of an integrated learning model, Lei et al. [8] constructed the chaotic grasshopper optimization algorithm to extract the financial features of enterprises through the complex data-preprocessing process, then used SVM to classify the data, and finally optimized it using the sticky mushroom algorithm to construct the SCF risk precautionary system. Table 1 presents a comparison of the models, accuracy, and sample sizes proposed by some scholars.

2.2. Blockchain-Based SCF Risk

The primary causes of SCF risk, such as repeated pledges and false warehouse receipts, are rooted in information asymmetry [6, 8]. Recognizing this, researchers have turned to blockchain technology. Its core architecture, which is based on Bitcoin, offers several key features. These include openness, transparency, immutability, decentralization, traceability, and shared maintenance. Together, these characteristics have been effectively utilized to mitigate SCF (Supply Chain Finance) risk [1, 3, 12]. Dong et al. [5] contend that blockchain technology facilitates the sharing of information in supply chain transactions, thereby enabling wider adoption of diverse financing tools within the supply chain. Natanelov et al. [14] demonstrated that blockchain's smart contract can shorten the cash flow cycle in the beef chain between Australia and China, while also reducing operational risk in blockchain-based SCF. Caniato et al. [2] com-

Table 1

Summary of each risk assessment model

Author	Research Method	Risk Type	Accuracy	Risk Classification	Number of Samples	Others
Zhang et al. [25]	Back Propagation Neural Network	Credit Risk	89.93%	Triple Classification	**189**	Sample Limited to the Automobile Industry
Sang [18]	SVM	Credit Risk	93.65%	Secondary Classification	**153**	Sample Limited to Automobile Equipment Manufacturing Industry
Zhu et al. [27]	Random Subspace-Real AdaBoost	Credit Risk	86.74%	Secondary Classification	**57**	
Lei et al [8]	Chaotic Grasshopper Optimization Algorithm + SVM + Sticky Mushroom Algorithm	Financial Risk	85.38%	Secondary Classification	A-Share Listed Companies in Shanghai and Shenzhen Stock Exchanges in the Last Three Years	Excluding Abnormal Data

pared SCF enabled by blockchain with traditional SCF and found that the former offers higher profits and lower operational risk. Wang et al. [21] argued that blockchain technology can streamline payments, manage cash flows, and cut operational costs by facilitating efficient data exchange, real-time processing, and transaction visualization. Furthermore, Min [13] utilized blockchain's distributed storage capabilities to overcome the mutual distrust prevalent in traditional centralized systems, transitioning from reliance on relationship-based trust to a more reliable data-based trust. This shift significantly streamlines SCF processes by eliminating unnecessary reviews and verifications, ultimately reducing transaction costs and time. Yu et al. [24] suggested that with blockchain technology, SMEs could independently validate business information's credibility and reliability, seek financing from banks, and significantly lower the platform's financial risk. Liu et al. [9] further integrated the Internet of Things with blockchain to simplify the supply chain's information flow, enabling direct communication among SCF participants and diminishing the risk associated with SCF. Soni et al. [19] proposed a decision-making framework to help SMEs develop sustainable SCF using Industry 4.0 technology. In a similar vein, Ahram et al. [1] and O'Leary [15] asserted that blockchain-enabled supply chain networks have shown improvements in transparency and accountability. Kshetri [7] employed multiple case studies to showcase blockchain's impacts on reducing costs, enhancing speed, reliability, risk mitigation, and flexibility in the supply chain.

Scholars have quantified SCF risk through AI methods and used blockchain to address information asymmetry and reduce risk, but the following shortcomings still exist:

1. Risk must be classified into more categories to accurately reflect the real risk status of enterprises [26].
2. Research on SMEs' credit risk is concentrated, and there are gaps in the research regarding other risk.
3. The number of research samples is insufficient, and the data can be easily tampered with, leading to low credibility of the model.
4. Most of the machine learning uses centralized architecture, which is vulnerable to hacking, resulting in a large amount of private data leakage.
5. The research on blockchain in SCF risk is mostly qualitative and less quantitative research [21].

In light of the above shortcomings, based on both domestic and foreign research foundations, this study established a blockchain-based SCF perception model. Firstly, to improve the risk quantification model and subdivide the risk into more categories. Secondly, to expand the sample size of the study and improve the representativeness and accuracy of the model. Thirdly, to utilize blockchain technology to enable the SCF risk to be monitored, assessed, warned and to form a comprehensive risk management framework for RE-SCF.

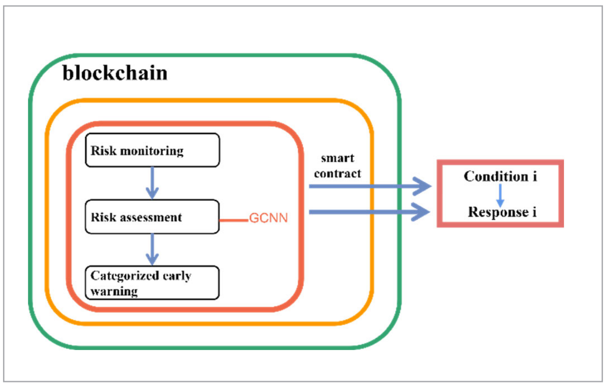
3. Intelligent Perception Model Framework for RE-SCF Risk

Smart contract is a set of digitally defined promises, automatically executed by the system when predefined contract terms are met [16]. The blockchain intelligent perception framework for RE-SCF risk established by integrating GCNN into blockchain smart contract is shown in Figure 1.

The framework of the intelligent perception model is explained below: the smart contract in the blockchain is used as the programming environment to establish an intelligent perception model integrating risk monitoring, assessment, and categorized early warnings. Risk monitoring determines the presence of risks in real estate supply chain enterprises. Risk assessment goes a step further by quantifying these risks.

Figure 1

The framework of the intelligent perception model for RE-SCF risk



Furthermore, categorized early warnings merge the risk levels of enterprises with their scale to issue tailored warnings. This approach not only strengthens the enterprises' implementation of risk management measures but also reduces the likelihood of SCF risk occurrences.

Smart contract in blockchain can reduce operational risk in RE-SCF [2, 4], but they have problems such as a lack of intelligence and flexibility, while AI has defects such as high computational cost, low resource utilization, and code vulnerability. By integrating blockchain with GCNN, the integrity, security, and validity of data can be effectively enhanced by the blockchain's consensus mechanism, asymmetric encryption, and hash algorithm [1, 20, 22]. This integration provides high-quality data sources and more distributed arithmetic power for AI, while AI can also add intelligent effects to smart contract, expanding and diversifying their functions and improving the blockchain's ability to process data [10]. Details are shown in Table 2.

As depicted in Figure 2, the blockchain architecture is stratified into six distinct layers: data layer, network layer, contract layer, incentive layer, consensus layer, and application layer. Within the contract layer, we have embedded functionalities for risk monitoring, risk assessment, and categorized early warnings, allowing for the full utilization of the advantages presented by the blockchain-enabled neural network.

Figure 2
Layer structure diagram of blockchain combined with

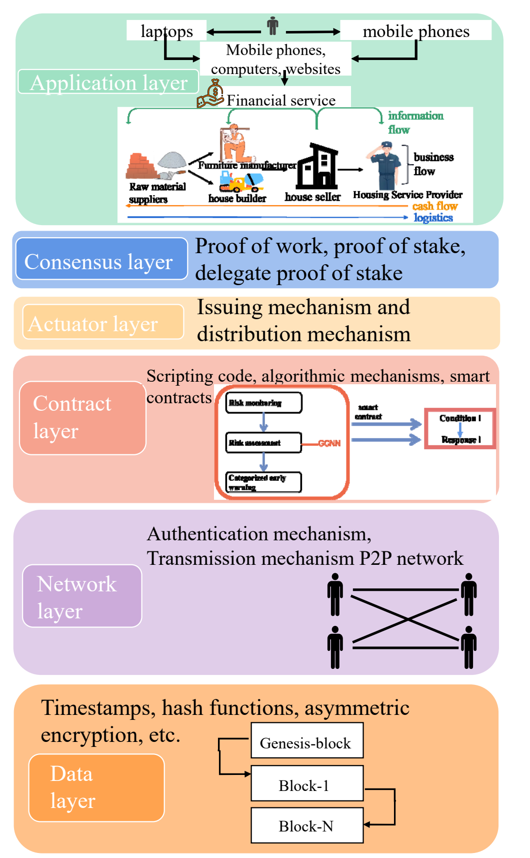


Table 2
Blockchain-enabled AI

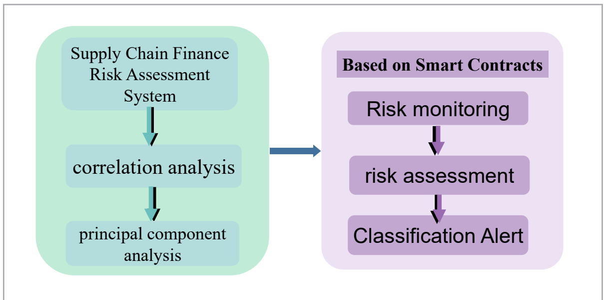
	Blockchain	AI	Blockchain + AI
RE-SCF data	1 RE-SCF data credibility assurance. 2 RE-SCF data privacy security and protection.	1 Depends on high-quality and reliable data. 2 requires multidimensional data under multiple data subjects.	Blockchain provides high-quality data sources for AI while ensuring data security and sharing.
RE-SCF evaluation algorithm	1 RE-SCF evaluation algorithm. 2 Lack of intelligence in smart contracts. 3 Lack of smart contract flexibility.	1 Builds complex contract code. 2 Solves the problem of prediction and analysis in the vulnerable domains of the human brain.	AI adds intelligent effects to blockchain smart contracts and improves the single functionality of the contract code.
RE-SCF data processing arithmetic	1 Decentralized distributed structure. 2 Shared computing resource environment.	1 Traditional Centralized Computing Cost is Too High. 2 Low resource utilization rate, easy-to-invade code vulnerability.	Under the premise of ensuring security, the distributed structure of blockchain provides more distributed arithmetic power for AI, which reduces redundant costs.

4. Establishment of Intelligent Perception Model for RE-SCF Risk

Based on the advantages of combining blockchain with AI as well as the perception framework proposed in Figure 1, the RE-SCF risk intelligent perception model was established as shown in Figure 3. Firstly, a risk assessment system tailored to the specific characteristics of China's real estate industry was established, integrating the industry's evaluation criteria into the enterprise's performance evaluation standards. Secondly, correlation analysis was used to remove the multicollinearity among the indicators. Then, the multi-dimensional indicators were fused using principal component analysis. Finally, a blockchain and a graph convolutional neural network were employed to establish an intelligent perception model, as shown in Figure 3. The specific content of the established risk intelligent perception model is outlined in Sections 4.1, 4.2, and 4.3.

Figure 3

Flow chart of RE-SCF risk intelligent perception



4.1. RE-SCF Risk Assessment Indicators Screening

4.1.1. Construction of Blockchain

This study takes government regulators and real estate enterprises as blockchain nodes, establishing the consortium chain. The data from the risk assessment system were merged on a per-enterprise basis and subsequently uploaded into the consortium chain.

Uploading RE-SCF data can leverage the data depository, cross-validation, and chronological relationship among blockchain technology timestamps. These features ensure the authenticity and reliability of the data in terms of completeness, reasonableness, and cause-and-effect logic. This process provides a real source of data for the subsequent risk monitoring, assessment, and categorized early warnings [11]. The addition of government nodes can provide real-time supervision, timely grasp of industry dynamics, and macro-control. The smart contract of the blockchain provides a programming environment for subsequent risk monitoring, assessment, and categorized early warnings while avoiding operational risk.

1. Refer to the financial institution risk management framework and the real estate industry evaluation system in the enterprise performance evaluation standard values, as published by the State Administration for Market Regulation and the Standardization Administration of China.
2. Referring to the risk management factors identified by Ying et al. [23], the current status of the enterprise was measured using four secondary indicators: profitability, solvency, operating capacity, and growth capacity. The current status of the supply chain was measured using the supply chain operation status and financing status.
3. The real estate industry is characterized by high leverage and high turnover. Additionally, before its collapse, Evergrande aggressively issued commercial papers and repeatedly delayed payments to downstream agents. To address these issues, additional metrics have been incorporated into the RE-SCF risk assessment system. These include the gearing ratio, cash ratio, days payable outstanding and days sales outstanding. These additions aim to more accurately reflect the capital status of enterprises and their position within the supply chain. The inclusion of the business cycle also indirectly reflects whether the enterprise has problems such as unfinished buildings and slow construction. Combining the three factors mentioned above, the established risk assessment system is shown in Table 3.

The preprocessing of data in Table 3 is performed by deleting most of the missing indicators. For example, 'Year of transaction' indicator, which is missing data for most of the companies, was deleted. For a small number of indicators with missing values, the industry average was used instead. when the 'gross margin' indicator is missing in parts of the manufacturing industry, the industry's average gross margin value can be used to fill in the missing data. The processing of the remaining indicators was consistent with the above principle.

Table 3
RE-SCF risk assessment indicators system

First-level indicators	Second-level indicators	Third-level indicators
RE-SCF Enterprise Risk	Profitability	Net Interest Rate, Gross Margin, Operating Income, Profit Scale
	Operating	Cash Current Debt Ratio, Inventory Turnover Ratio, Accounts Receivable Turnover Ratio
	Solvency	Cash Current Ratio, Quick Ratio, Cash Ratio, Gearing Ratio
	Growth Capacity	Total Assets, Size, Operating Income Growth Rate
RE-SCF Risk	Operational Condition	Economic Boom Degree, average revenue-growth rate across the industry, Business Cycle
	Financing Status	Days Sales Outstanding, Transaction Years, Transaction Frequency, Days Payable Outstanding

Based on the preprocessed data, it is found that the data did not adhere to the normal distribution. Consequently, the Spearman correlation test was performed on the third-level indicators under the same second-level indicator. The correlation between the variables was used in Equation (1) to calculate the correlation coefficient ρ. When $|\rho|$ is located in the 1.0–0.8 range for a very strong correlation and 0.6–0.8 for a strong correlation. To avoid multicollinearity, indicators with strong correlations are deleted.

$$\rho = 1 - \frac{6\sum d^2}{n(n^2-1)} \tag{1}$$

Where 'ρ' denotes the Spearman correlation coefficient, 'd' represents the rank difference between x and y, and 'n' indicates the sample capacity.

4.2. Multidimensional Indicators Fusion for RE-SCF Risk

Multidimensional indicators fusion plays a key role in providing more comprehensive and accurate analysis, enhancing decision support. Especially in the field of RE-SCF with complex and changing environments, it can effectively identify, capture, and assess potential risk factors. Based on the results of the correlation analysis, the risk assessment indicators were deleted; the RE-SCF risk assessment indicators system was established. The indicators were fused using principal component analysis (PCA), and the fused indicator was used as the criteria for RE-SCF risk assessment. The specific steps are as follows:

1. To eliminate differences in dimensions and numerical ranges among various datasets while mitigating issues like gradient vanishing and explosion, normalization was applied. The normalization formula is shown below:

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}, \tag{2}$$

where 'x_i' represents the ith x and 'x_i'' the value of the ith x after normalization.

2. PCA was performed on the data, according to the empirical principle given by Kaiser [6]. When the KMO value is > 0.5 and the sig value is < 0.01, it is suitable to utilize PCA to fuse the multidimensional data and extract the key components.
3. The importance ranking of the extracted components was obtained from the fragmentation diagram extracted by PCA. The multidimensional data in the risk assessment indicators system was fused by using the matrix of component score coefficients. The fused indicators can comprehensively and effectively reflect the RE-SCF risk.

4.3. Construction of Intelligent Perception Model for RE-SCF Risk

4.3.1. RE-SCF Risk Monitoring

RE-SCF risk monitoring used the smart contract in the blockchain as the technical support and determines risk thresholds for the fusion of the indicators obtained. Establishing these risk thresholds helps identify potential risks within enterprises. Should any risks be identified, a risk assessment is then conducted to further quantify the risk levels faced by real estate enterprises.

4.3.2. RE-SCF Risk Assessment

GCNN is used to uncover data patterns based on the risk indicators system. Then a risk assessment model was built, which rates the enterprise risk level. When the data is input into the model, GCNN performs a risk assessment on the enterprise and uses the output of different labels to represent various risk levels of the enterprise. The process of building a risk assessment model is shown below:

1 Parameter Settings

The parameters to be used in the risk assessment section and their meaning are shown in Table 4.

Adjacency matrix: matrix with edge links

$$\begin{array}{cccccc} & n_1 & n_2 & n_3 & \cdots & n_{398} \\ n_1 & 1 & 0 & 0 & \cdots & 0 \\ n_2 & 0 & 1 & 0 & \cdots & 0 \\ n_3 & 1 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ n_{398} & 0 & 0 & 0 & \cdots & 0 \end{array}$$

Degree matrix:

diagonal matrix formed by node self-loop

$$\begin{array}{cccccc} & n_1 & n_2 & n_3 & \cdots & n_{398} \\ n_1 & 1 & 0 & 0 & \cdots & 0 \\ n_2 & 0 & 1 & 0 & \cdots & 0 \\ n_3 & 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ n_{398} & 0 & 0 & 0 & \cdots & 1 \end{array}$$

2 Data Segmentation

Enterprises were represented as nodes, enterprise-trading relationships as edges, and indicators within the RE-SCF risk assessment system as feature data. The ratio of the training set was selected based on when the model achieved the highest accuracy rate.

3 Selection of activation function

The common activation functions were averaged three times, and the best activation function was selected based on the accuracy of the activation function.

4 Convolution operation

Based on the algorithm and training time considerations, this study uses three convolutional layers. Through the nodes and edges to establish graph data, as well as node feature data and graph data into the convolution layers for convolution operations. The general operations process is shown in Figure 4.

Figure 4

Convolutional algorithm

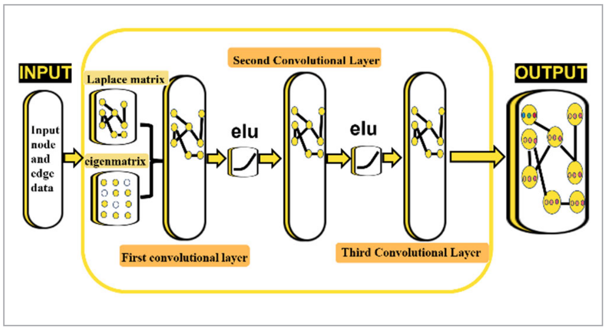


Table 4

Parameter-setting

Parameter	Meaning	Parameter	Meaning
N	Node Set	$\hat{m}_t$	m_t Bias Correction
n	Node	$\hat{v}_t$	v_t Bias Correction
t_n	Supervised Data	Lr	Learning Rate
y_n	Prediction Data	ε	A Minimum Constant, about 10^{-7}
g_t	Time Step Gradient at Time t	Laplace matrix	Degree Matrix–Adjacency Matrix
grad	Gradient	Output is '0'	High-Risk Firms
L	Loss Function	Output is '1'	Standard Firms
W_t	Weight at The Time t	Output is '2'	Low-Risk Firms
m_t	Exponential Moving Average of the Gradient at t Time, with $m_0 = 0$	β_1, β_2	The Exponential Decay Rate, A Default Value of 0.9 for β_1, Default Value of 0.999 for β_2
v_t	Exponential Moving Average of the Squared Gradient at Time t $v_0 = 0$	F_1	Results of The Principal Component Analysis

Calling up the training set, Equation (3) was used to calculate the outputs and labels of the training set. These calculated labels were then used to compare the labels of the test set and original data. his comparison aimed to calculate the space occupied by test set labels to obtain the outputs.

$$E= -\sum_{n=1}^{N} t_n ln y_n \tag{3}$$

Cross-entropy formula

5 Back propagation

The model was initialized with a gradient before the next iteration. To prevent the previous gradient from affecting the current gradient, the gradient operation must be performed. The weights were updated by back propagation using the Adam optimizer so that the weight matrix in the convolutional network was updated in real time to further improve the accuracy.

$$g_t = grad\ L(W_t), \tag{4}$$

$$m_t = \beta_1 m_{t-1} + (10 - \beta_1) g_t, \tag{5}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^{\ 2}, \tag{6}$$

$$\widehat{m_t} = \frac{m_t}{1-\beta_1{}^t}, \tag{7}$$

$$\widehat{v_t} = \frac{v_t}{1-\beta_2{}^t}, \tag{8}$$

$$W_t = W_{t-1} - \frac{lr*\widehat{m_t}}{(\sqrt{\widehat{v_t}}+\varepsilon)}. \tag{9}$$

Adam's process formula

The different learning rate of the optimizer determined the magnitude of updating each weight in the gradient direction, as shown in Table 5.

A learning rate that is either too large or too small can hinder to the improvement of the model's accuracy. Therefore, the learning rate at the highest accuracy and the lowest loss rate of the model was selected for the Adam optimizer.

6 Perform iterations

To prevent the model from overfitting or underfitting, it is necessary to iterate the back propagation step and the convolution operation step. According to the reflection of the number of iterations in the accuracy of the model, the number of iterations was selected, and the weights were updated after each iteration to improve the accuracy of the model.

7 Comparative study of AI models

After the above steps, the accuracy of the model was obtained, and the results of GCNN, MLP, and SVM were compared in terms of accuracy, mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). This comparison was to verify the performance of the GCNN model. The relevant explanations about MSE, RMSE, and MAE are as follows: The y_i in Equations (10)-(12) represents the true value, $\hat{y}_i$ represents the predicted value, and n is the amount of data.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2, \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|(y_i - \hat{y}_i)\right|}, \tag{11}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|(y_i - \hat{y}_i)\right|. \tag{12}$$

4.3.3. RE-SCF Risk Categorized Early Warnings

In SCF, enterprises are closely connected, and the "bonding" effect of finance makes it easier for risk to spread. SCF risk will be magnified exponentially, especially the risk of core enterprises, which are more likely to be transmitted to other enterprises in the supply chain, and losses will increase exponentially. The risk of the core enterprises has a significant impact on the overall risk of SCF, while the risk of the marginal micro- and small enterprises has little impact on it.

Table 5

Learning rate setting

Learning rate	Advantages	Disadvantages
Large	It can speed up the convergence of weights, which is conducive to improving the accuracy.	Accuracy is not stable.
Small	The speed of weight convergence is more stable, and the accuracy fluctuates less.	The accuracy is not High enough.

After predicting the enterprise risk using a GCNN risk assessment model, the model acted accordingly. If the core enterprise risk result is standard (with an output label of 1) or high-risk (with an output label of 0), it will automatically return the risk assessment result, provide an early warning and remind the enterprise to take measures in time. Similarly, if the risk results of medium-sized enterprises, small enterprises, and micro enterprises are high-risk, they will also receive warnings.

5. RE-SCF Case Study

This section analyzes the real estate supply chain, using data from the Wind database spanning the last three years. It covers a total of 1,203 data entries across various sectors, including the real estate industry, construction manufacturing, wood processing, financial industry, and warehousing and transportation agency.

5.1. Deletion and Fusion of Risk Assessment Indicators

5.1.1. Correlation Analysis

The data were preprocessed, and since it does not satisfy normal distribution, the Spearman correlation test was performed on the third-level indicators within the same second-level indicator. The results are presented in Table 6. Profit size, net interest rate, gross margin, and operating income are strongly correlated or have a highly significant correlation. To prevent pseudo-correlation, a partial correlation analysis was conducted, the results are shown in Table 7.

Table 7 reveals that the net interest rate is weakly correlated with operating income by ignoring the

Table 6

Correlation analysis

	Operating Income	Profit Size	Gross Margin	Net Interest Rate
Operating Income	1	**0.705**	**0.870**	**0.688**
Profit Size	0.705	1	**0.667**	**0.993**
Gross Margin	0.870	0.667	1	**0.639**
Net Interest Rate	0.688	0.993	0.639	1
		Accounts Receivable Turnover Ratio	Inventory Turnover Ratio	
Accounts Receivable Turnover Ratio		1	-0224	
Inventory Turnover Ratio		-0.224	1	
		Gearing Ratio	Cash Current Ratio	
Gearing Ratio		1	0.583	
Cash Current Ratio		0.583	1	
	Total Assets	Size	Operating Income Growth Rate	
Total Assets	1	0.112	0.281	
Size	0.112	1	0.039	
Operating Income Growth Rate	0.281	-0.039	1	
		Days Sales Outstanding	Days Payable Outstanding	
Days Sales Outstanding		1	0.312	
Days Payable Outstanding		0.312	1	
		Business Cycle	Economic Boom Degree	
Business Cycle		1	0.047	
Economic Boom Degree		0.047	1	

Table 7
Biased correlation analysis

Control Variables			Net Interest Rate	Gross Margin	Operating Income	Control Variables			Net Interest Rate	Gross Margin	Operating Income
Profit Size	Net Interest Rate	Correlation	1.000	-.337	-.023	Gross Margin	Net Interest Rate	Correlation	1.000	-.293	.983
		Significance (two-tailed)	.	.000	.484			Significance (two-tailed)	.	.000	.000
		Degrees of Freedom	0	889	889			Degrees of Freedom	0	889	889
	Gross Margin	Correlation	-.337	1.000	.887		Operating Income	Correlation	-.293	1.000	-.400
		Significance (two-tailed)	.000	.	.000			Significance (two-tailed)	.000	.	.000
		Degrees of Freedom	889	0	889			Degrees of Freedom	889	0	889
	Operating Income	Correlation	-.023	.887	1.000		Profit Size	Correlation	.983	-.400	1.000
		Significance (two-tailed)	.484	.000	.			Significance (two-tailed)	.000	.000	.
		Degrees of Freedom	889	889	0			Degrees of Freedom	889	889	0

Table 8
Supply chain finance risk assessment system

First-level Indicators	Second-level Indicators	Third-level Indicators
Real Estate Supply Chain Enterprise Risk	Profitability	Operating Income (x_1), Net Interest Rate (x_2)
	Operating	Receivable Turnover Ratio (x_3) Inventory Turnover Ratio (x_4)
	Solvency	Cash Current Ratio (x_5), Gearing Ratio (x_6)
	Growth Capacity	Total Assets (x_7), Size (x_8) Operating Income Growth Rate (x_9)
Real Estate Supply Chain Risk	Operational Condition	Business Cycle (x_{10}), Economic Boom Degree (x_{10})
	Financing Status	Days Sales Outstanding (x_{12}) Days Payable Outstanding (x_{13})

effect of profit scale and gross margin. This suggests net interest rate is pseudo-correlated with operating income. Consequently, net interest rate and operating income were retained, and profit scale and gross margin were deleted. The assessment indicators system obtained after the correlation analysis is shown in Table 8.

5.1.2. Principal Component Analysis Fusion Indicators

1. Using formula (2), the data for the aforementioned indicators were normalized.
2. The data were subjected to a PCA. From Table 9, it can be seen that KMO value = 0.6 > 0.5, and sig value

Table 9
Results of KMO and Bartlett's test

Results of KMO and Bartlett's Test		
KMO Number of Sampling Suitability		.600
Bartlett's Test of Sphericity	Approximate Chi-square	4268.396
	Degree of Freedom	78
	Significance	.000

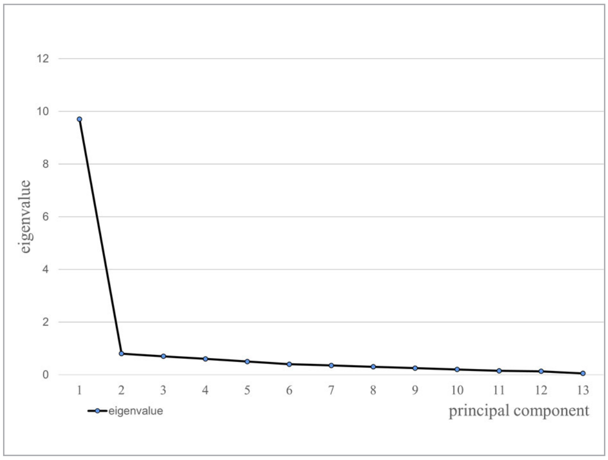
= 0.000 < 0.01. According to the empirical principle of Kaiser[6], it is appropriate to apply PCA for the fusion of multidimensional indicators, facilitating the extraction of the primary component.

3 As can be seen in Figure 5, the cumulative contribution of the first principal component extracted by PCA has the highest eigenvalue with 93.6% information retention. Using Table 10, the multi dimensional data in the risk assessment indicator system was fused, and the first principal component obtained is given by the following step.

4 From table 10, it can be concluded that:

$$F_1 = 0.351x_1 + 0.351x_2 - 0.023x_3 + 0.022x_4 + 0.042x_5 - 0.017x_6 + 0.028x_7 - 0.009x_8 + 0.035x_9 - 0.041x_{10} + 0.007x_{11} - 0.106x_{12} + 0.348x_{13}$$

Figure 5
Gravel diagram



5.2. Intelligent Perception Model for RE-SCF Risk

5.2.1. Construction of Blockchain

Using the above data as a basis for merging by enterprise, the enterprise and the government were used as nodes to establish a consortium chain. Part of the block data of the established consortium chain are shown below. Each block generally comprises two parts, the header and the body. The header includes the version, nonce, Merkle root, timestamp, hash value of the previous block, hash value of the current block, among other details. Some of the block data are shown in Table 11. The ‘index’ identifies the block’s position in the blockchain; ‘timestamp’ records the time when the block data was written; ‘nonce’ is a random number, in mining to search for a nonce value that satisfies the condition; and ‘hash’ is a fixed-length output gen-

Table 10
Matrix of component score coefficients

	1	2	3	4	5
Operating Income (x_1)	.351	.010	-.023	.055	.011
Net Interest Rate (x_2)	.351	.014	-.063	-.003	.004
Receivable Turnover Ratio (x_3)	-.023	.044	.088	-.234	.165
Inventory Turnover Ratio (x_4)	.022	-.054	.073	-.074	.848
Cash Current Ratio (x_5)	.042	-.033	-.466	.012	-.038
Gearing Ratio (x_6)	-.017	-.024	.493	.002	.107
Total Assets (x_7)	.028	-.161	-.033	.548	.006
Size (x_8)	-.009	-.130	.014	-.220	.019
Operating Income Growth Rate (x_9)	.035	.496	-.072	-.200	-.042
Business Cycle (x_{10})	-.041	.083	.143	.535	.055
Economic Prosperity (x_{11})	.007	.490	.055	.057	.005
Days Sales Outstanding (x_{12})	-.106	-.106	.250	-.041	-.400
Days Payable Outstanding (x_{13})	.348	.033	.009	-.011	.022

Table 11
Part of the block

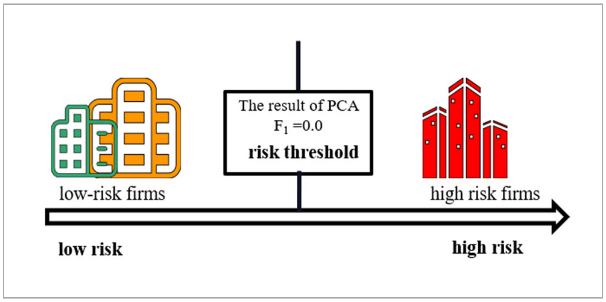
Index	Timestamp	Data	Nonce	Hash	Previous Hash
0	2023-10-08 16:40:01.342236	Genesis Block	0.09146469573129068	b466f949001ec2a1576218700c0997bdedc1dfaae2183194446cdd79526e3696	
1	2023-10-08 16:40:16.076399	Short Name ...2022-Assets and Liabilities Enterprise 1...0.947774	0.019663870258609828	a7b52a19cf9ef3d4307eae5eb6292f68f0492b05b94a3281dafe31df7ffa5e0d	b466f949001ec2a1576218700c0997bdedc1dfaae2183194446cdd79526e3696
2	2023-10-08 16:40:26.341499	Short Name ...2022-Assets and Liabilities Enterprise 1...0.947774	0.9278943290609113	3a41ade686cbcb460071cf4067d737064737d3be62604624184fe358962397e8	a7b52a19cf9ef3d4307eae5eb6292f68f0492b05b94a3281dafe31df7ffa5e0d

erated using the SHA-256 function. 'Previous Hash' denotes the hash value of the previous block.

5.2.2. RE-SCF Risk Monitoring

This study focuses on the RE-SCF risk of enterprises as the research objective using the blockchain's smart contract to delineate the risk threshold for F_1. This approach facilitates the dynamic monitoring of enterprise risk. Based on the "Standard Values for Enterprise Performance Evaluation" issued by the State-owned Assets Supervision and Administration Commission of the State Council, the specific delineation is shown in Figure 6.

Figure 6
Risk threshold



5.2.3. RE-SCF Risk Assessment

Taking the real estate supply chain as a sample, GCNN was employed to establish a risk assessment model. When the data is input, GCNN conducts a risk assessment of the enterprise. The risk assessment model-building processes are illustrated below.

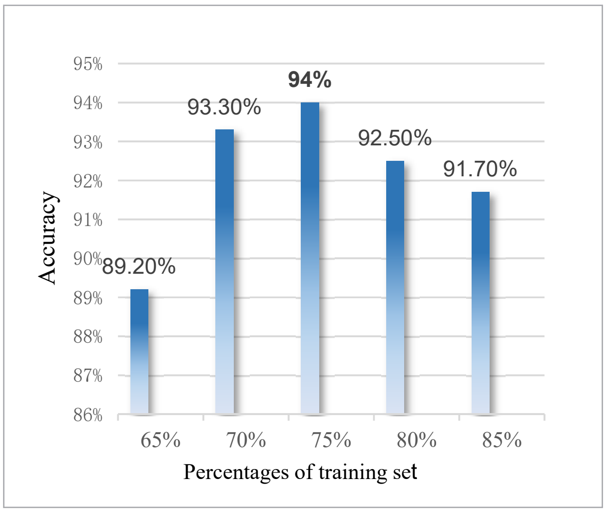
1 Data Segmentation

As depicted in Figure 7, the model has the highest accuracy when the training set share is 75%, so the number of training and test sets are selected as in Table 12.

Table 12
Percentage of training set and test set

	Category	Percentage	Quantity
398	Trainning set	75%	298
	Test set	25%	100

Figure 7
Accuracy with different percentages of the training set

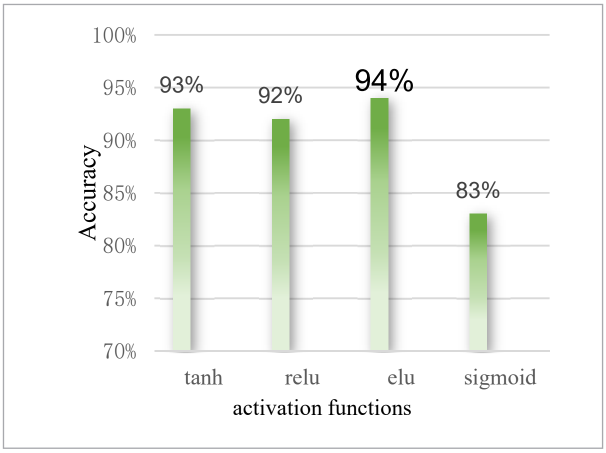


2 Selection of Activation Functions

The common activation functions were averaged three times, as shown in Figure 8. Elu has the highest accuracy, so it was chosen as the activation function of the model.

Figure 8

Accuracy with different activation functions

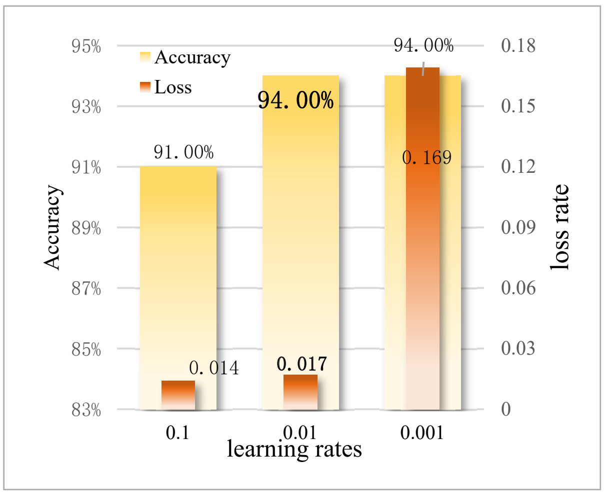


3 Back Propagation

After each output result was obtained, the weights were updated through backpropagation with Adam's optimizer. As shown in Figure 9, the accuracy is plotted on the left vertical axis and the loss rate is plotted on the right vertical axis. The learning rate of 0.01 yields the highest accuracy and the smallest loss rate, so the learning rate of Adam was taken as 0.01.

Figure 9

Accuracy and loss rate for different learning rates



4 Perform Iterations

As shown in Figure 10, after 1500 iterations, the accuracy of the model is stable at about 94%, which also represent the shortest time to achieve this accuracy. Therefore, the number of iterations of the model was selected as 1500. In comparison with MLP and SVM, and the comparison results are shown in Figure 11. Here, the accuracy is plotted on the left vertical axis, and MAE, MSE, and RMSE are plotted on the right vertical axis. The accuracy of the GCNN model is higher than the others, and the error is lower, which is a better performance.

Figure 10

Accuracy at different numbers of iterations

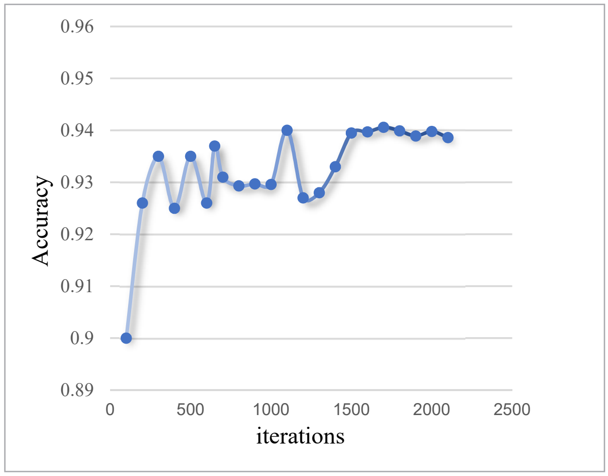
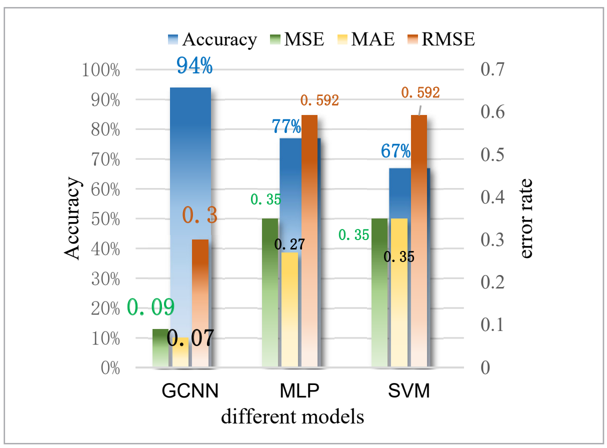


Figure 11

Comparison results of different models



5.2.4. Categorized Early Warnings of RE-SCF Risk

The results of the partial categorization of 398 pieces of data are shown in Table 13, from which it can be seen that Pudong Construction, Feiliks, Yongan Forestry, and core high-risk, core standard, and other high-risk enterprises were warned. A combination of classified early warnings and smart contract solves the problem of untimely risk warnings. Timely warnings to high-risk enterprises significantly reduce the risk in RE-SCF, thereby enhancing the real estate finance ecosystem's operation.

Table 13
Partial categorization results

Enterprise size	Risk level	Enterprise name		
Core (large) enterprises	low risk	Long Yuan Construction	......	Greenland Holdings
	Standard	Pudong Construction	......	Anhui Construction Engineering Group
	High risk	Zhuhai Winbase International Chemical Tank Terminal	......	Feiliks
Small enterprises	low risk	Beijing Airport High-tech Park	......	Chengbang Eco-Environment
	High risk	Yongan Forestry		Quishui Science and Technology
Micro-enterprises	low risk	Huili Building Materials		Yayi Metal Technology

6. Conclusion

A significant number of bankruptcies have emerged in China's real estate industry. Traditional risk assessment exhibits flaws such as imprecise risk categorization, slow assessment speed, delayed warnings, and data vulnerability to tampering. Against this backdrop, this study utilizes smart contract in blockchain and GCNN to propose an intelligent risk-perception model that integrates risk monitoring, assessment, and categorized warnings. A comparison of GCNN with MLP and SVM reveals that GCNN's accuracy reaches 94%, while MLP is at 77%, and SVM at 67%, indicating GCNN's superiority over other models.

The model established in this paper has the following advantages:

1. Utilizing the blockchain's transparent nature, it facilitates multi-level information flow, thus reducing the probability of information silo. Additionally, the immutable characteristic of blockchain overcomes the traditional risk assessment model's vulnerability to data tampering and low credibility.
2. By expanding the research sample size and subdividing risk into more categories, the model's representativeness and accuracy are enhanced.
3. The GCNN technology in blockchain smart contract provides faster assessments than expert-judgment evaluations. It also offers precise risk levels, quantifying the probability of enterprises being classified as high-risk, thus providing a quantitative basis for financial regulation.
4. Smart contract automatically issues alerts based on risk assessment results, providing a quicker warning mechanism compared to traditional methods that rely on monitoring repayment behaviors and market fluctuations. This feature enables a swifter response to potential risk.

Acknowledgement

This study was financed by the National Natural Science Foundation of China (71974091), Hunan Social Science Foundation Base Project (22JD033), Hunan Science and Technology Innovation Platform Open Subject Project (KFKB2210), and General Project of Scientific Research Program of Hunan Provincial Department of Education (22C0218).

References

1. Ahram, T., Sargolzaei, A., Sargolzaei, S., Daniels, J., Amaba, B. Blockchain Technology Innovations. IEEE Technology & Engineering Management Conference (TEMSCON). IEEE, 2017, 137-141. https://doi.org/10.1109/TEMSCON.2017.7998367
2. Caniato, F., Gelsomino, L. M., Perego, A., Ronchi, S. Does Finance Solve The Supply Chain Financing Problem? Supply Chain Management: An International Journal, 2016, 21(5), 534-549. https://doi.org/10.1108/SCM-11-2015-0436
3. Chen, C., Chen, P., Lin, C. An Ensemble Classifier for Stock Trend Prediction Using Sentence-level Chinese News Sentiment and Technical Indicators. International Journal of Interactive Multimedia and Artificial Intelligence, 2022, 7(3), 53-64. https://doi.org/10.9781/ijimai.2022.02.004
4. Chen, Y. J., Tsai, H., Liu, Y. F. Supply Chain Finance Risk Management: Payment Default in Tourism Channels. Tourism Economics, 2018, 24(5), 593-614. https://doi.org/10.1177/1354816618762187
5. Dong, L., Qiu, Y., Xu, F. Blockchain-enabled Deep-tier Supply Chain Finance. Manufacturing & Service Operations Management, 2023, 25(6), 2021-2037. https://doi.org/10.12 87/msom.2022.1123
6. Du, M., Chen, Q., Xiao, J., Yang, H., Ma, X. Supply Chain Finance Innovation Using Blockchain. IEEE Transactions on Engineering Management, 2020, 67(4), 1045-1058. https://doi.org/10.1109/TEM.2020.2971858
7. Kshetri, N. 1 Blockchain's Roles in Meeting Key Supply Chain Management Objectives. International Journal of Information Management, 2018, 39, 80-89. https://doi.org/10.1016/j.ijinfomgt.2017.12.005
8. Lei, Y., Qiaoming, H., Tong, Z. Research on Supply Chain Financial Risk Prevention Based on Machine Learning. Computational Intelligence and Neuroscience, 2023, 2023. https://doi.org/10.1155/2023/6531154
9. Liu, L., Zhang, J. Z., He, W., Li, W. Mitigating Information Asymmetry in Inventory Pledge Financing Through the Internet of Things and Blockchain. Journal of Enterprise Information Management, 2021, 34(5), 1429-1451. https://doi.org/10.1108/JEIM-12-2020-0510
10. Liu, Y., Yu, F. R., Li, X., Ji, H., Leung, V. C. M. Blockchain and Machine Learning for Communications and Networking Systems. IEEE Communications Surveys & Tutorials, 2020, 22(2), 1392-1431. https://doi.org/10.1109/COMST.2020.2975911
11. Liu, Z., Cruz, J. M. Supply Chain Networks with Corporate Financial Risks and Trade Credits Under Economic Uncertainty. International Journal of Production Economics, 2012, 137(1), 55-67. https://doi.org/10.1016/j.ijpe.2012.01.012
12. Maestro, A. A., Sanjua′n-Marti′nez, O., Teredesai, A. M., Díaz, V. G. Blockchain Based Cloud Management Architecture For Maximum Availability. International Journal of Interactive Multimedia and Artificial Intelligence, 2023, 8(1), 88-94. https://doi.org/10.9781/ijimai.2023.02.002
13. Min, H. Blockchain Technology for Enhancing Supply Chain Resilience. Business Horizons, 2019, 62(1), 35-45. https://doi.org/10.1016/j.bushor.2018.08.012
14. Natanelov, V., Cao, S., Foth, M., Dulleck, U. Blockchain Smart Contracts for Supply Chain Finance: Mapping the Innovation Potential in Australia-China Beef Supply Chains. Journal of Industrial Information Integration, 2022, 30, 100389. https://doi.org/10.1016/j.jii.2022.100389
15. O'Leary, D. E. Configuring Blockchain Architectures for Transaction Information in Blockchain Consortiums: the Case of Accounting and Supply Chain Systems. Intelligent Systems in Accounting, Finance and Management, 2017, 24(4), 138-147. https://doi.org/10.1002/isaf.1417
16. Pournader, M., Shi, Y., Seuring, S., Koh, S. L. Blockchain Applications in Supply Chains, Transport and Logistics: A Systematic Review of the Literature. International Journal of Production Research, 2020, 58(7), 2063-2081. https://doi.org/10.1080/00207543.2019.1650976
17. Rezaei, S., Shokouhyar, S., Zandieh, M. A Neural Network Approach for Retailer Risk Assessment in the Aftermarket Industry. Benchmarking: An International Journal, 2019, 26(5), 1631-1647. https://doi.org/10.1108/BIJ-06-2018-0162
18. Sang, B. Application of Genetic Algorithm and BP Neural Network in Supply Chain Finance Under Information Sharing. Journal of Computational and Applied Mathematics, 2021, 384, 113170. https://doi.org/10.1016/j.cam.2020.113170
19. Soni, G., Kumar, S., Mahto, R.V., Mangla, S., Mittal, M. L., Lim, W. M. A Decision-Making Framework for Industry 4.0 Technology Implementation: The Case of FinTech and Sustainable Supply Chain Finance for SMEs. Technological Forecasting and Social Change, 2022, 180,121686. https://doi.org/10.1016/j.techfore.2022.121686

20. Tan, L., Xiao, H., Yu, K., Aloqaily, M., Jararweh, Y. A Blockchain-empowered Crowdsourcing System for 5G-enabled Smart Cities. Computer Standards & Interfaces, 2021, 76, 103517. https://doi.org/10.1016/j.csi.2021.103517
21. Wang, L., Luo, X. R., Lee, F., Benitez, J. Value Creation in Blockchain-driven Supply Chain Finance. Information & Management, 2022, 59(7), 103510. https://doi.org/10.1016/j.im.2021.103510
22. Xiao, P., Salleh, M. I., Zaidan, B. B., Xuelan, Y. Research on Risk Assessment of Blockchain-driven Supply Chain Finance: A Systematic Review. Computers & Industrial Engineering, 2023, 176, 108990. https://doi.org/10.1016/j.cie.2023.108990
23. Ying, H., Chen, L., Zhao, X. Application of Text Mining in Identifying the Factors of Supply Chain Financing Risk Management. Industrial Management & Data Systems, 2020, 121(2), 498-518. https://doi.org/10.1108/IMDS-06-2020-0325
24. Yu, Y., Huang, G., Guo, X. Financing Strategy Analysis for a Multi-sided Platform with Blockchain Technology. International Journal of Production Research, 2021, 59(15), 4513-4532. https://doi.org/10.1080/00207543.2020.1766718
25. Zhang, L., Hu, H., Zhang, D. A Credit Risk Assessment Model Based on SVM for Small and Medium Enterprises in Supply Chain Finance. Financial Innovation, 2015, 1(1), 1-21. https://doi.org/10.1186/s40854-015-0014-5
26. Zhang, W., Yan, S., Li, J., Tian, X., Yoshida, T. Credit Risk Prediction of SMES in Supply Chain Finance by Fusing Demographic and Behavioral Data. Transportation Research Part E: Logistics and Transportation Review, 2022, 158, 102611. https://doi.org/10.1016/j.tre.2022.102611
27. Zhu, Y., Xie, C., Wang, G. J., Yan, X. G. Predicting China's SME Credit Risk in Supply Chain Finance Based on Machine Learning Methods. Entropy, 2016, 18(5), 195. https://doi.org/10.3390/e18050195