Retraction

Retracted: Enterprise Financing Risk Control of Machine Learning Combined with Blockchain Technology

Advances in Multimedia

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Li, "Enterprise Financing Risk Control of Machine Learning Combined with Blockchain Technology," *Advances in Multimedia*, vol. 2022, Article ID 3084196, 15 pages, 2022.

Research Article

Enterprise Financing Risk Control of Machine Learning Combined with Blockchain Technology

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In order to scientifically and reasonably control the financing risk of supply chain enterprises and minimize the financing risk of the enterprises, this paper introduces the relevant theories of machine learning algorithm and blockchain technology, proposes an enterprise financing risk control model based on the combination of machine learning algorithm and blockchain technology, and uses system dynamics to dynamically evaluate the system risk. Finally, the specific changes of each subsystem over time are obtained. Through the risk evaluation results, it can be seen that the risk level of the blockchain system has decreased from the initial 4.3 to 0.3 after two months of transition, and the risk control effect is very significant.

1. Introduction

In recent years, with the continuous development of China's social economy and the acceleration of industrial transformation and upgrading, the development model of the financial industry has become more and more diversified, and at the same time, enterprises are facing higher and higher financing risks in the process of development. With the continuous development of blockchain technology, there are more and more research studies on various specific scenario applications related to blockchain technology. The emergence of these applications has a positive impact on the operation mode of supply chain finance at the current stage. With its own characteristics, the emergence and development of blockchain technology can better meet the requirements of enterprise financing risk control and can better control the financial risk of supply chain. Based on the technical characteristics of the blockchain and taking enterprise financing risk control as the research direction, this paper proposes an enterprise financing risk control model based on the combination of machine learning algorithm and blockchain technology.

2. Literature Review

Domestic: some scholars summarized the impact of blockchain technology on the current operation mode of China's financial industry and various difficulties faced in the promotion of the financial industry and advocated to improve the scenario application of the blockchain in the financial field through science and technology such as the Internet of things; it is expected that the blockchain will have a significant impact on the financial sector. By reducing operating costs and improving operational efficiency, the regulatory capacity can be further improved. Blockchain technology records all transactions in real time through a distributed ledger and can never be modified, so as to achieve the effect of self-letter of credit. According to statistics, the research proportion of blockchain technology in supply chain finance is higher than that in other financial fields. Relevant literature shows that the blockchain can optimize the operation process of supply chain financial business and can reduce the difficulty and cost of financing enterprises. Some scholars tried to apply blockchain technology to factoring business and describe the improvement in its traditional model. They believed that blockchain

technology would help supply chain finance break through the inherent obstacles; Hernández et al. [1] summarize the impact of the application of blockchain technology on the participating nodes of supply chain finance, so as to describe the economic value of blockchain technology [1]; Payedi-marri et al. [2] believe that blockchain technology will help enterprises maximize the value of data, make up for the disadvantages of traditional supply chain finance, and optimize the risk control system of the whole supply chain finance. By studying the characteristics of blockchain technology, such as decentralization, nontampering, mul-tinode consensus mechanism, and distributed accounting, believes that blockchain technology will help traditional supply chain finance overcome the shortcomings of poor link transmission, lack of moral hazard constraints, low transaction efficiency and so on [2]. Moon et al. [3] found that the traditional supply chain finance has the problem of "information island," that is, it is difficult to integrate the four streams and the information flow is not smooth, which makes it difficult to carry out the traditional supply chain finance business and greatly increases the risk of fraud. If blockchain technology is adopted, such problems can be perfectly solved because of its decentralized, data tamper proof, and other characteristics that can ensure the integration of four flows in the supply chain finance and can open up the information closed loop of all participants, and provide a new solution for supply chain risk control [3].

In foreign countries, some scholars have found that blockchain technology can greatly improve the efficiency of the operation and can simplify the steps of transaction through an online operation, so as to reduce labor costs; when describing the application of blockchain technology in the financial field, Ezzaouini et al. [4] pointed out that the blockchain is actually a distributed database with asymmetric encryption algorithm, which has a very important application value in the financial field [4]. Blockchain technology has gradually expanded from the basic field of finance to its surrounding industries, especially through the natural matching with the field of supply chain finance. It uses its characteristics of data transmission and storage that cannot be modified to increase the credit of small and medium-sized enterprises in the chain, so as to make it easier to obtain financing. At the same time, it uses the automatic execution mechanism of smart contract to make up for the disadvantages of traditional supply chain financial risk control; Tedre et al. [5] summarized the application scenario blueprint of blockchain technology in supply chain finance, as well as the landing restrictions faced in this field and the great innovation that will be brought to this field; by studying the characteristics of blockchain technology, be-lieves that it can effectively make up for many disadvantages of the traditional supply chain finance and uses blockchain technology to formulate a set of implementation strategy of asset securitization for accounts receiving financing. Finally, he also depicts a beautiful blueprint for the combination of blockchain technology and supply chain finance [5].

3. Machine Learning Algorithm

3.1. Logistic Regression. Logical regression is often used to deal with classification problems, which has evolved through linear regression. Linear regression is used to find the linear relationship between the output eigenvector $h(x)$ and the input sample matrix X, and the coefficient W satisfies $h(x) = WX$. However, when the output eigenvector $h(x)$ is discrete, the linear regression method fails. In order to solve this problem, the solution that scholars think of is that when the output eigenvector is a discrete value, $h(x)$ is transformed into $g(h(x))$ again. If the value of $g(h(x))$ is category A in a real interval and category B in another real interval, and so on, a classification model will be obtained. When there are only two categories of results, it is a binary classification model. The goal of linear regression is to fit the distribution of samples in space with the linear combination of features. The independent variable X is the feature, $h(x)$ is the label, and W represents the weight corresponding to the feature. Thus, the linear regression formula can be expressed as

$$h(x) = w_0 + w_1 x_1 + w_2 x_2 + \cdots w_n x_n = W^T x. \quad (1)$$

On the basis of linear regression, the Sigmoid function is introduced to map all its output values between [0,1]. The formula of the Sigmoid function is as follows:

$$g(z) = \frac{1}{1 + e^{-z}}. \quad (2)$$

The Sigmoid function image is shown in Figure 1 and its value range [0, 1] can be found.

$g(z)$ can map the continuous value between 0 and 1 and can substitute the linear regression expression into $g(z)$, as shown in the following formula:

$$g(z) = g(W^t x). \quad (3)$$

The objective function of logistic regression is shown in the following formula:

$$h_w(x) = g(W^T x)$$
$$= \frac{1}{1 + e^{-W^T x}}. \quad (4)$$

From the objective function of logistic regression in formula (4), it can be found that no matter what value x takes, its value range stays within the interval of [0, 1]. Generally, for a binary classification problem, the result is only 0 or 1, where 0 corresponds to "no" and 1 corresponds to "yes." For the output results between (0, 1), you can set the threshold to classify the output results greater than 0.5 as 1 classification and those less than 0.5 as 0 classification, so as to achieve the purpose of secondary classification. The maximum likelihood probability is constructed as shown in the following formula:
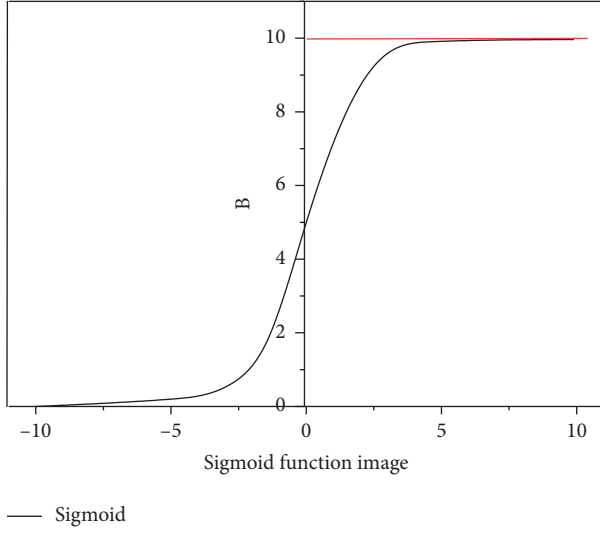
Figure 1: Sigmoid function image.

$$L(w) = \Pi_{i=1}^{N} \left(h_w\left(x^i\right) \right)^{y^i} * \left(1 - h_w\left(x^i\right) \right)^{1-y^i}. \tag{5}$$

The gradient descent method is used to solve the optimal parameter w, which is abbreviated as

$$J(w) = \frac{1}{m} l(w). \tag{6}$$

The problem can be transformed into a multiclassification problem through binary classification. One vs the rest is usually used to realize multiclassification. The principle is that when there may be multiple labels in the sample, each class in the multiclass is treated as a binary classification to obtain w binary logistic regression classifiers. The i-th classifier can predict whether each sample can be classified as class i. When training the classifier, it is necessary to reorganize the labels into class i labels and nonclass i labels, so as to achieve the situation that each sample has multiple multiclass labels and achieve the goal of multiclassification task.

3.2. Gradient Lifting Algorithm.

GBDT is essentially an additive model, that is, the algorithm uses multiple decision trees to combine together, and each tree will get a prediction result. GBDT adds and sums the results of each tree and takes the final summation result as the final result.

In the iterative process of GBDT, the forward distribution algorithm is usually adopted. For example, assuming that the result of GBDT after the last iteration is $F_{m-1}(x)$, and $L = (y, F_{m-1}(x))$ is the loss function after the iteration, the goal of the next iteration is to find a decision tree, $\rho_m g_m(x)$, so that the next loss reaches the minimum value as shown in the following formula:

$$L\left(y, F_{m-1}(x)\right) + \rho_m g_m(x). \tag{7}$$

According to the characteristics of GBDT, it can be represented as shown in the following formulas:

$$F^* = \arg \min E_{x,y}\left[L\left(y, F_{m-1}(x)\right)\right], \tag{8}$$

$$F\left(x; \rho_m, a_m\right) = \sum_{m=0}^{m} \rho_m h\left(x; a_m\right). \tag{9}$$

For the estimation of $g_m(x)$, the decision tree is used to approximate $g_m(x)$, so that the distance between the two is as close as possible, and there are many ways to measure the distance, such as logarithmic error and so on. The following derivation will be based on the logarithmic loss function, as shown in the formula:

$$L(y, F) = \log\left(1 + \exp\left(-2yF\right)\right), y \in \{-1, 1\}. \tag{10}$$

First, solve F_0 so that its partial derivative is 0, as shown in formulas (11)–(14):

$$F_0 = \arg \min \sum_{i=1}^{N} L\left(y_i, F\right), \tag{11}$$

$$\frac{\partial \sum_{i=1}^{N} L\left(y_i, F\right)}{\partial F} = 0, \tag{12}$$

$$\sum_{i=1}^{N} \frac{\exp\left(p - y_i 2F\right)\left(-y_i 2\right)}{1 + \exp\left(p - y_i 2F\right)} = 0, \tag{13}$$

$$F_0(x) = \frac{1}{2} \log \frac{1 + \overline{y}}{1 - \overline{y}}. \tag{14}$$

Then, estimate $g_m(x)$ as follows:

$$\begin{aligned} g_m\left(x_i\right) &= -\frac{\partial F\left(y_i, F\right)}{\partial F}\Big|_{F=F_{m-1}} \\ &= \frac{2y_i \exp\left[-2y_i F_{m-1}(x_i)\right]}{1 + \exp\left[-2y_i F_{m-1}(x_i)\right]} \\ &= \frac{2y_i}{1 + \exp\left[-2y_i F_{m-1}(x_i)\right]}. \end{aligned} \tag{15}$$

Then, the Newton iterative method is used to approximate the step size in the descending direction. This step is omitted in the process of algorithm implementation because different values can be assigned to the parameters according to the shrink strategy to achieve the effect of setting the step size, as shown in the following formulas:

$$f(r) = \sum_{x_i \in R_{jm}} \log\left[1 + \exp\left(-2y_i(F_{m-1}(x) + r)\right)\right], \tag{16}$$

$$f\prime(r) = \sum_{x_i \in R_{jm}} \frac{-2y_i}{1 + \exp\left(-2y_i(F_{m-1}(x) + r)\right)}, \tag{17}$$

$$f\prime\prime(r) = \sum_{x_i \in R_{jm}} \frac{2y_i \exp\left[2y_i(F_{m-1}(x) + r)\right]}{\left[1 + \exp\left(-2y_i(F_{m-1}(x) + r)\right)\right]^2}, \tag{18}$$

$$\gamma_{jm} \approx \gamma_0 - \frac{f'(r_0)}{f''(r_0)} = \frac{\sum_{x_i \in R_{jm}} \widetilde{y}_i}{\sum_{x_i \in R_{jm}} |\widetilde{y}_i| (2 - |\widetilde{y}_i|)}. \tag{19}$$

Finally, the formula can be represented as

$$F_m(x) = F_{m-1}(x) + \gamma_{jm}. \tag{20}$$

4. Construction of Enterprise Financing Financial Risk Evaluation System Based on Machine Learning and Blockchain Technology

4.1. Types of Enterprise Financing Risks. When a company receives all of its financial assets fairly, operational risk is the total risk of the transaction and is borne entirely by the shareholders. Corporate financial risk 2 includes the liquidity of assets. Principal loans and interest are usually paid in cash. Therefore, even if the entity's profits are good, its ability to pay its financial loans and interest on time in accordance with the terms of the agreement depends on the entity's adequate financial timeliness and total capital investment. Cash flow indicates solvency and liquidity indicates the solvency of assets. If a company does not know when its investment is wrong, its lending policy is too high, and it will face many financial problems, such as needing a lot of cash and paying high interest. In particular, business financial risk consists of the following four factors [6].

4.1.1. Enterprise Financing Risk I: Enterprise Operation Risk. Business risk is the risk of production, operations, and activities that directly affect the uncertainty of an entity's pre-tax and interest income. Operational risk is different from financial risk but it affects financial risk. When a company receives all of its financial assets fairly, operational risk is the total risk of the transaction and is borne entirely by the shareholders. As companies expand their access to equity and credit costs, investor returns will increase and the risks will outweigh operational risks. The difference is financial risk. If the company is mismanaged and operating costs are not enough to pay the interest, members' income will decline and interest will be paid along with the investment. In extreme cases, the company will have to make a decision and promote its business [7].

4.1.2. Enterprise Financing Risk II: Capital Liquidity. The principal and interest on the debt are usually repaid in cash (cash capital). Therefore, even if the entity's profits are good, its ability to pay its financial loans and interest on time in accordance with the terms of the agreement depends on the entity's adequate financial timeliness and total capital investment. Cash flow indicates solvency and liquidity indicates the solvency of assets. If a company thinks its investment is wrong, or if its lending policy is too high, or if it does not know what income it is earning when it pays its principal and interest, it will face financial difficulties. During this period, the market is able to recognize its assets

in order not to incur losses but the volatility of different assets varies. Of these, the liquidity of the cash cell is the strongest, while the liquidity of fixed assets is the weakest. The total liquidity of an entity's assets is different, i.e., the proportion of different assets in total assets varies due to financial adequacy. The total liquidity of an entity's assets is high and there are many high liquid assets, but the financial risk is low; conversely, the financial risk is higher when the total capitalization of goods is weak and there are many low assets. Many businesses lose money not because they do not have it but because they cannot finish it in the short term. As a result, they are forced to pay their debts on time and have to declare their business [8].

4.1.3. Enterprise Financing Risk III: Volatility Risk of Financial Market. The financial market is a place of financing. Trading costs are affected by financial markets. For example, interest rates depend on capital and demand in the financial markets after a loan is obtained, and changes in the financial system, such as changes in access to the exchange rates, can increase the risk of financial transactions. Companies often use it to finance short-term loans, while hard financing and spending lead to higher and lower interest rates when short-term loans increase. Also, some companies lose their business and trade because they cannot pay the interest on the loan [9].

4.1.4. Enterprise Financing Risk: A Trap in the Process of Enterprise Financing. The emergence of various financial instruments such as investment, fairness, and private investment has led to many financial and economic developments for businesses, but they are always dealing with problems, and some incorrect financial information can lead to big losses for businesses. For example, in the current financial market, some fraud in the name of investment occurs one after another. They will first attract businesses with better circumstances and then ask the companies to develop business plans or attorneys to inspire. First, they will pay a part of the cost, and then pay for the inspection, research, and reception [10].

4.2. Analysis of Financial Business System Based on Blockchain Technology

4.2.1. System Architecture. The general architecture of the system is shown in Figure 2.

In terms of blockchain network architecture and blockchain module connection, the network section is responsible for connecting the service interface module, which must link the financial service history of the supply network to the blockchain service. Blockchain networks typically include member management, blockchain services, data distribution, and code networking services. Among them, blockchain service mainly realizes the communication management function of P2P and the underlying consensus mechanism; member management mainly includes member registration, member audit, member authentication, and
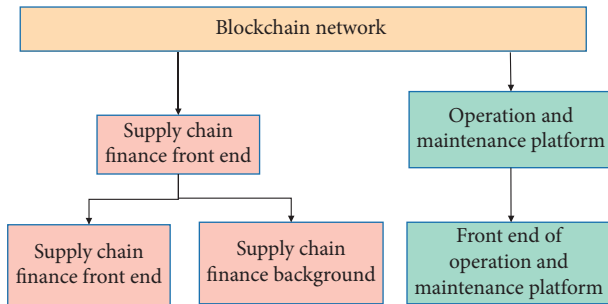
Figure 2: General system architecture.

other functions; the distributed ledger stores the transaction data on the chain; the chain code implements the functions of chain code container and chain code deployment. The service interface includes four modules, namely, scheduling control, authority management, certificate management, and fiiric SDK. The interaction between the four modules and the supply chain financial background is realized by relevant interfaces, so that certificates and authorities can be well managed [11].

4.3. System Business Module

4.3.1. Supplier Management Process. First, after the supplier enters the supply chain financial system, it calls the enterprise information writing interface of the service platform to write the enterprise information into the blockchain ledger; the core enterprise can then call the interface for querying enterprise information on the service platform, query the supplier list, select the supplier with transaction, and write the transaction information into the blockchain through a series of steps after the transaction [12]. The management process is shown in Figure 3.

4.3.2. Order Transaction Process. After the supplier delivers goods, it calls the relevant interface to write the information about the shipment into the blockchain. After receiving the goods, the core enterprise calls the relevant interface to confirm the completion of the transaction on the blockchain, as shown in Figure 4.

4.3.3. Capital Flow Process. When there is a financing demand, the supplier, that is, the financing enterprise, will put forward a loan demand to the bank because of the shortage of funds. The bank will query the enterprise information and transaction information on the chain through the relevant interface and review it to decide whether to finance. If so, the financing enterprise will get the funds and this round of transaction will be completed. After the financing period expires, the core enterprise will transfer this round of financing payment to the bank, and all information at this stage will be recorded in the blockchain [13]. The business flow chart of capital flow is shown in Figure 5.

4.4. Construction of Supply Chain Financial Risk Evaluation System on Blockchain. In order to clarify the risks of supply chain finance in the block, the risk analysis process of this paper is shown in Figure 6.

This set of evaluation system is based on the principles of comprehensiveness, scientificity, legitimacy, or operability, pertinence, quantitative, and qualitative combination. Among them, scientificity refers to the scientific selection of the indicators and scientific classification and sorting, so that the indicators do not repeat each other, and the theory should be practical [14].

In each dimension, the part related to the blockchain is black and bold.

First, the selection of indicators for the construction of macro and industrial risk evaluation system is shown in Table 1.

Second, the selection of indicators for the construction of credit risk evaluation system is shown in Table 2.

Third, the selection of indicators for the construction of supply chain relationship risk evaluation system is shown in Table 3.

Fourth, the selection of indicators for the construction of pledge risk evaluation system is shown in Table 4.

Fifth, the selection of indicators for the construction of operational risk assessment system is shown in Table 5.

Sixth, selection of indicators for the construction of blockchain system risk evaluation system is shown in Table 6.

5. Enterprise Financing Risk Evaluation on Blockchain Based on System Dynamics

5.1. Applicability of System Dynamics. The fuzzy comprehensive evaluation method and the analytic hierarchy process are static evaluation of the financial risk of the supply chain on the blockchain, and their evaluation basis can only reflect the risk of the supply chain finance at a certain time. The supply chain financial system on the blockchain is a mobile system. Various transactions are going on continuously, and the values of relevant indicators and parameters are constantly changing. Therefore, the static evaluation system can make an initial value for the risk in a certain period of time but cannot reflect the risk value of supply chain finance on the blockchain in real time. Based on this, this paper uses system dynamics to further dynamically analyze the supply chain finance on the blockchain, so as to achieve real-time risk control [15].

The operation steps of system dynamics are as follows:

(1) Find out the problem

(2) Analyze the causes of the problem and put forward assumptions

(3) Establish computer simulation model

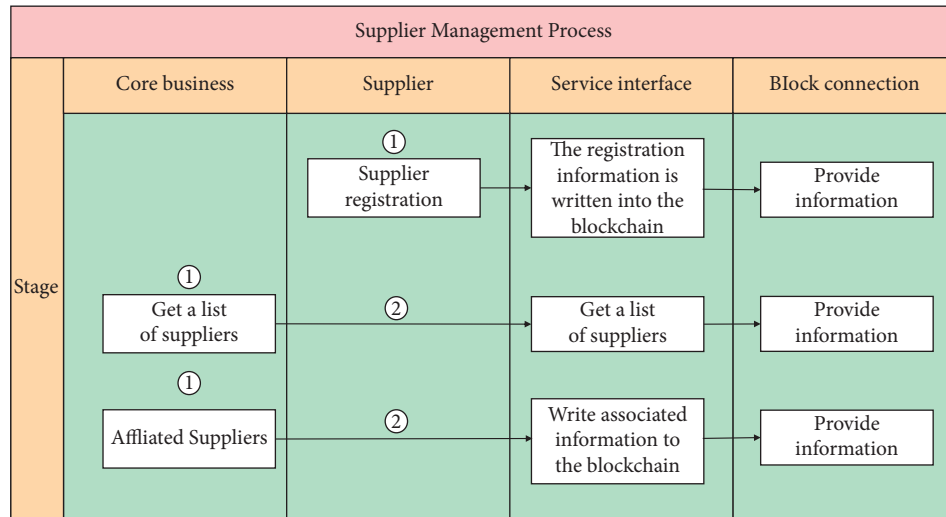(4) Conduct model testing to ensure that the model can simulate the behavior in the real world
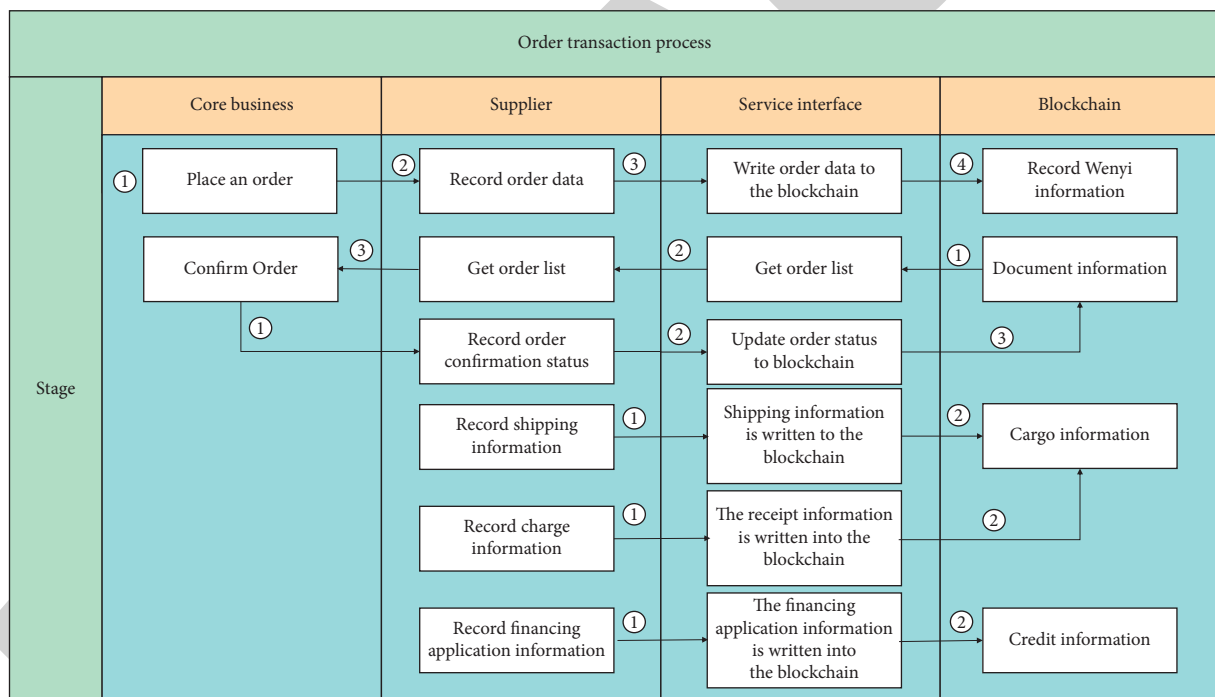
Figure 3: Supplier management process.

Figure 4: Order transaction process.

(5) Multischeme test to find out the local optimal scheme of the problem

(6) Implementation of the scheme

As the risk of supply chain finance on the blockchain is multidimensional and dynamic, when the environment of any participant changes, the overall risk level will also change. The sources of each risk are different. Each source point can be regarded as a subsystem. Each subsystem is not only dynamic internally but also dynamic in the interaction between systems. Therefore, this chapter uses the system power to simulate the

supply chain financial risk on the blockchain and will establish a more effective supply chain financial risk control mechanism according to the simulation results.

5.2. Causality Diagram of Each Subsystem. The supply chain financial risk on the blockchain is mainly affected by six factors (see Figure 7). These six dimensions are the macro and industrial risk, credit risk, supply chain relationship risk, pledge risk, operational risk, and the blockchain system risk [16].
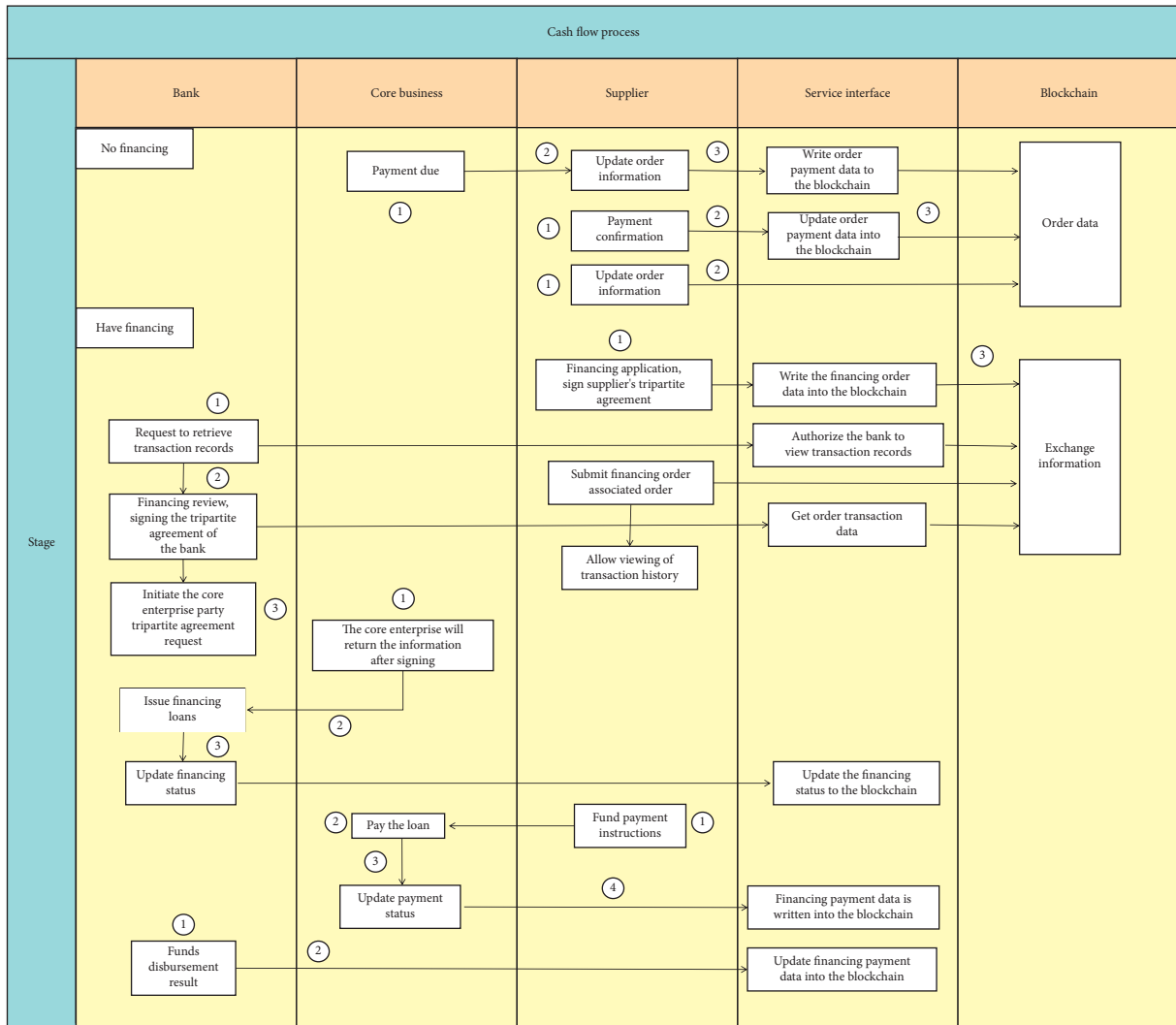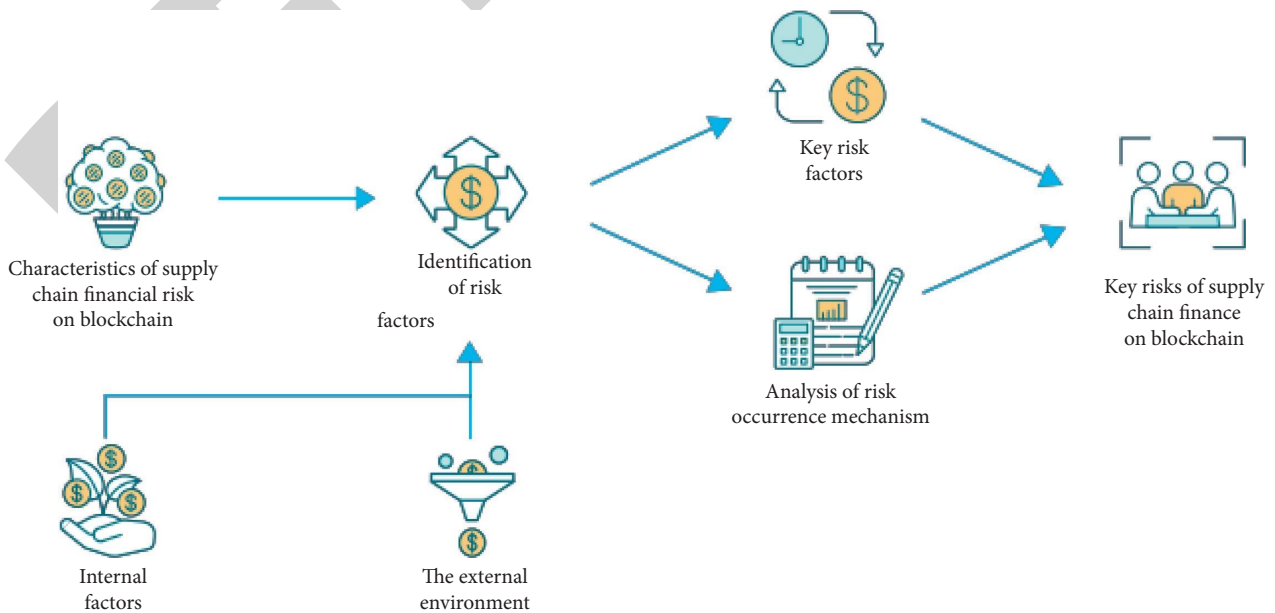
Figure 5: Capital flow process.

Figure 6: Risk analysis flow chart.

TABLE 1: Construction indicators of the macro and industrial risk evaluation system.

Primary index		Macro and industry risks
Secondary index	Macro environment	Industry development prospect
Tertiary indicators	Macroeconomic conditions and blockchain policies	Industry competition intensity

TABLE 2: Indicators of the credit risk evaluation system.

Primary index	Macro and industry risks		
Secondary index	Financing enterprise quality	Solvency of financing enterprises	
Tertiary indicators	Employees' understanding of blockchain Management quality Enterprise scale, and financial disclosure quality	Sales profit margin Return on net assets Current ratio Quick ratio	Enterprise operating capacity cash Current to current mobilization debt ratio Interest cover Fixed fee reimbursement ratio Asset liability ratio Long-term asset suitability ratio

Primary index	Macro and industry risks		
Secondary index	Counterparty profitability	Development potential of financing enterprises	Counterparty credit status
Tertiary indicators	Industry status Counterparty sales profit margin Return on net assets of counterparties Counterparty quick ratio Counterparty fixed fee reimbursement	Growth rate of total assets Net profit growth rate Sales revenue growth rate	Previous performance Credit rating External guarantee

TABLE 3: Risk evaluation index of supply chain relationship.

Primary index	Supply chain relationship risk	
Secondary index	Closeness of supply chain and blockchain	Financing enterprise status
Tertiary indicators	Supply chain time Transaction frequency on blockchain Default	Product price advantage Product substitutability Throughput

TABLE 4: Risk evaluation index of the pledge.

Primary index	Risk of pledge	
Secondary index	Sales risk	Logistics warehousing risk
Tertiary indicators	Stability of sales channels Stability of sales customers; Scope of sales area; Market bulk density; Sales accounting period;	Vulnerability and perishability of goods Degree of commodity standardization on blockchain Logistics enterprise level Supporting storage conditions Commercial insurance of pledge

TABLE 5: Indicators of the operational risk assessment system.

Primary index	Operational risk		
Secondary index	Process risk	Personnel risk	Technical risk
Tertiary indicators	Maturity of blockchain process design Standardization degree of blockchain process Standardization degree of blockchain information	Personnel fraud Human operation blockchain Proficiency	Abnormal trading system Abnormal financing system Abnormal payment system Abnormal logistics system Network security Blockchain transaction history data exception

Primary index	Operational risk		
Secondary index	Financing approval risk	Payment risk	Warehouse supervision risk
Tertiary indicators	Smart contract vulnerability Bank approval Bank audit Blockchain platform audit	Payment data Out of account Payment collection	Take delivery of goods Deliver goods Warehouse receipt error

TABLE 6: Indicators of blockchain system evaluation system.

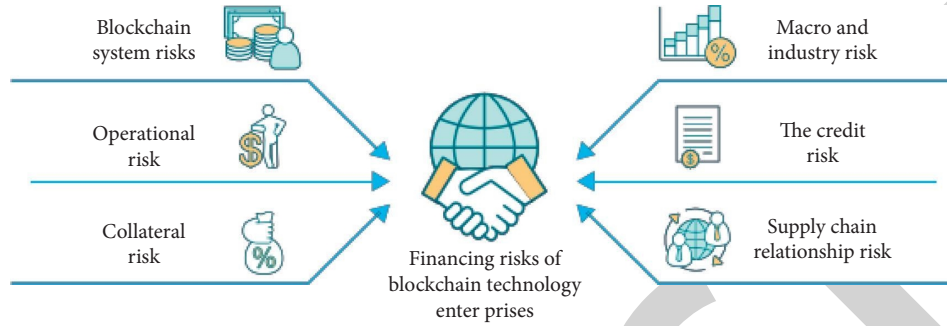| First-level indicator	New technology is risky	Security risk	Stability and reliability
Secondary indicators	Investment failure	Data security	Ecosystem matures
Three-level indicator	Market mismatch	Wrong implementation	Extensibility

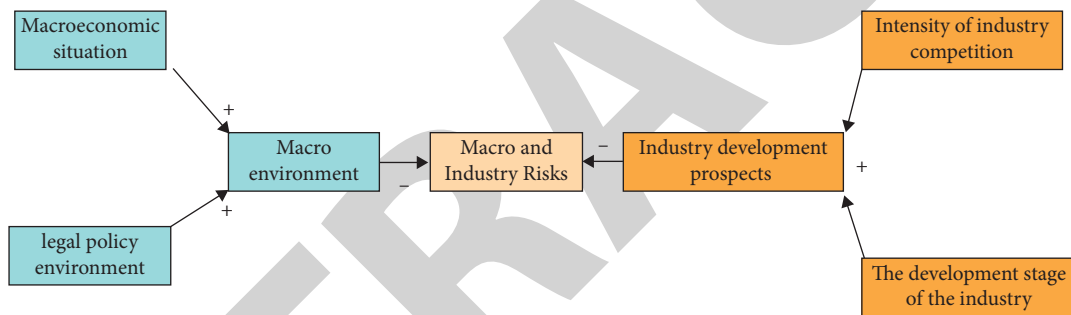FIGURE 7: Financial risk dimensions of supply chain on the blockchain.

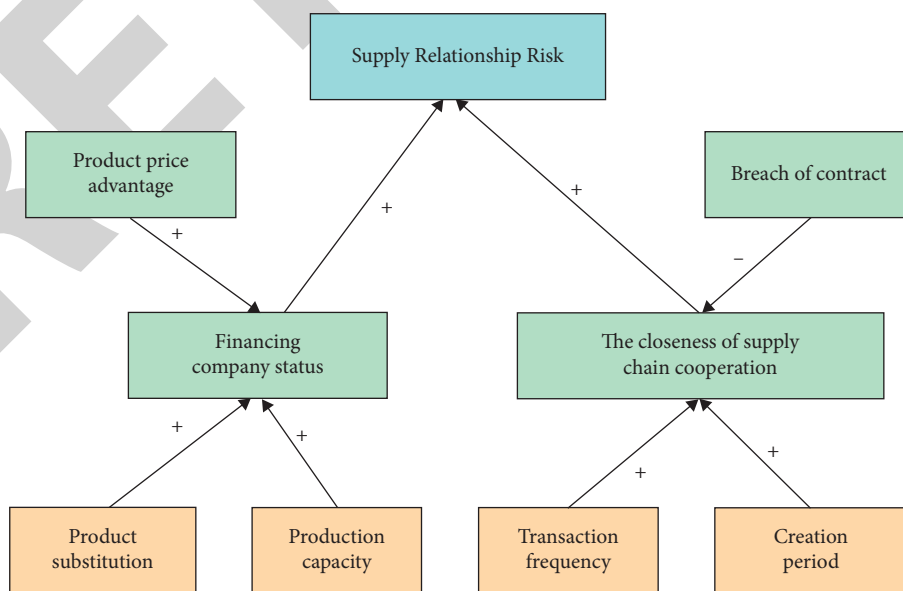FIGURE 8: Causality diagram of macro and industrial risks.

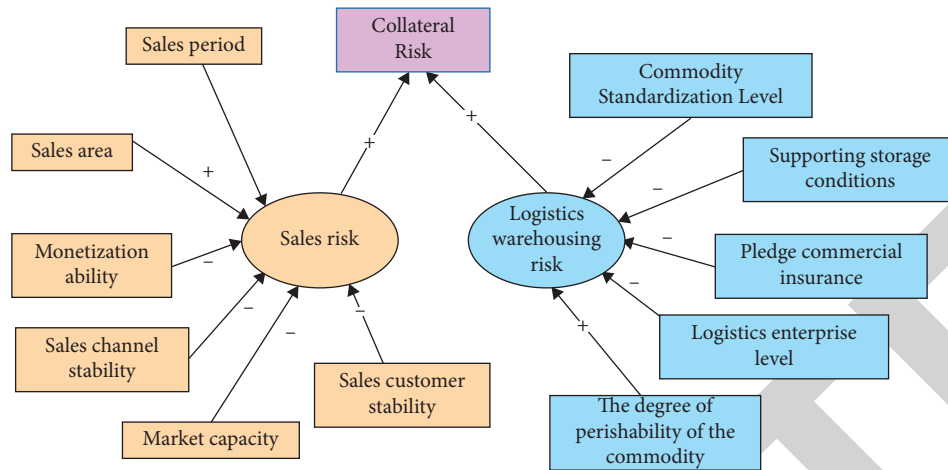FIGURE 9: Causality diagram of supply chain risk.
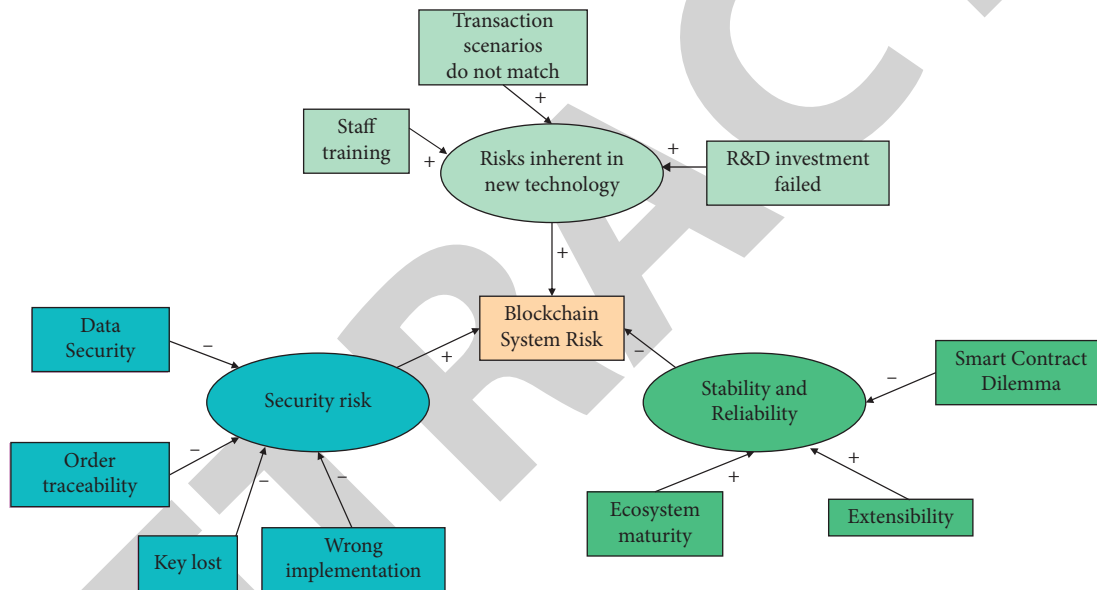
Figure 10: Causality diagram of pledge risk.

Figure 11: Causality diagram of blockchain system risk.

Table 7: Financial level variables of supply chain on the blockchain.

Variable scene name	Variable code	Variable star description
Macro and industry risks	$L1$	The unit is dimensionless. The higher the score, the higher the risk level
Credit risks	$L2$	Dimensionless. The greater the score, the higher the risk
Supply chain relationship risk	$L3$	Dimensionless. The greater the score, the higher the risk
Risk of pledge	$L4$	Dimensionless. The greater the score, the higher the risk
Operational risk	$L5$	Dimensionless. The greater the score, the higher the risk
Blockchain system risk	$L6$	Dimensionless. The greater the score, the higher the risk

The following describes the system relationship of the four main modules.:

(1) Macro and industry risk subsystem (see Figure 8)
(2) Supply chain relationship risk subsystem (see Figure 9)
(3) Collateral risk subsystem (see Figure 10)
(4) Blockchain system risk subsystem (see Figure 11)

5.3. *Variable Set of the System Dynamics Model.* Assign values to various variable types, including the horizontal variable (represented by box), rate variable, auxiliary variable (storing intermediate process), and constant variable [17].

5.3.1. *Horizontal Variable Set.* Level variable can be called integral variable in mathematics. The general solution is to integrate other variables in time [18], as shown in Table 7:

TABLE 8: Financial risk flow of supply chain on blockchain.

Variable scene name	Variable code	Variable star description
Macro and industry risk reduction scenario	R1	Reduction of macro and industrial risks per unit time
Credit risk reduction	R2	Reduction of credit risk level per unit time
Supply chain relationship risk reduction	R3	Reduction of relationship level reduction per unit time
Increased risk of pledge	R4	Increase of collateral risk per unit time
Increase in operational risk	R5	Increase in operational risk per unit time
Increase in blockchain system	R6	Increase in blockchain system risk per unit time
Reduction in blockchain system	R7	Reduction in blockchain system risk per unit time

TABLE 9: Auxiliary variables of supply chain financial risk system on the blockchain.

Variable scene name	Variable code	Variable star description
Solvency of financing enterprises	11	The unit is dimensionless. The greater the score, the higher the solvency
Financing enterprise status	12	Dimensionless. The higher the score, the higher the status
Sales risk	13	Dimensionless. The higher the score, the higher the sales risk
Technical risk	14	Dimensionless. The greater the score, the higher the technical risk
Financing approval risk	15	Dimensionless. The higher the score, the higher the approval risk
Bank status	16	Dimensionless. The higher the score, the higher the bank status
Supply chain financial risk on blockchain	17	Dimensionless. The higher the score, the higher the risk

TABLE 10: Initial value of subordinate index.

Primary index	Relative weight	Membership level						
		Y1	y2	y3	y4	y5	y6	y7
I1	0.058	0.000	0.000	0.000	0.075	0.375	0.241	0.308
I2	0.200	0.007	0.171	0.235	0.368	0.193	0.003	0.020
I3	0.221	0.000	0.184	0.296	0.239	0.217	0.053	0.007
I4	0.102	0.000	0.149	0.302	0.272	0.204	0.068	0.003
I4	0.149	0.022	0.098	0.236	0.383	0.198	0.054	0.006
I6	0.270	0.007	0.171	0.235	0.368	0.193	0.003	0.020

5.3.2. Rate Variable Set. Rate variable (Rite Viriille) is the amount of change in unit time. It is generally the inflow rate and outflow rate set for the source and the drain of horizontal variable, as shown in Table 8.

5.3.3. Auxiliary Variable Set. Auxiliary variables are the intermediate products of the horizontal variables, speed variables and other types of variables. The existence of auxiliary variables can effectively reflect some delay and nonlinear changes in the feedback system, which plays an important role in the simulation of real activities, as shown in Table 9.

5.3.4. Constant Set. The constant set in the model is the amount that does not change with time in the process of model simulation. If the constant changes, it will automatically change to another simulation. Changing the constant value can get many different simulations, and each simulation result set can be compared. The constants are divided into general constants and ratio constants. General constants are set objectively and are reasonably analyzed according to the actual survey data. The ratio constant is the ratio of the two variables in the system [19].

5.4. System Simulation Operation

5.4.1. Purpose

(1) Verify the impact intensity of different primary indicators on the financial risk of the supply chain on the blockchain, so as to determine the change of the total risk with the change of each primary indicator risk [20].

(2) By changing different initial values for simulation, the different trends of system risk with different initial values are obtained, which provides a basis for the preliminary preparation of the blockchain system.

(3) Observing the risk development of each subsystem and the development trend of supply chain finance on the blockchain can well control the total risk.

5.4.2. Determination of Initial Value of Simulation Operation. In order to test the feasibility of the simulation system, it is necessary to simulate the simulation system. The risk evaluation value comes from the reference of relevant references, and the initial value of system risk evaluation can be obtained by referring to the previous theoretical research and analysis [21]. This simulation sets the financing period as two months, as shown in Tables 10 and 11.

Table 11: Initial value of secondary index membership.

Secondary index	Relative weight	Membership level						
		Y1	Y2	Y3	Y4	Y5	Y6	Y7
$I11$	0.250	0.000	0.000	0.000	0.300	0.200	0.367	0.133
$I12$	0.750	0.000	0.000	0.000	0.000	0.433	0.200	0.367
$I21$	0.071	0.061	0.388	0.330	0.159	0.000	0.000	0.000
$I22$	0.194	0.000	0.011	0.675	0.442	0.346	0.015	0.000
$I24$	0.101	0.000	0.050	0.050	0.270	0.600	0.000	0.000
I25	0.272	0.000	0.375	0.320	0.150	0.050	0.000	0.000
I28	0.333	0.000	0.107	0.24	0.555	0.096	0.000	0.000
I31	0.333	0.000	0.291	0.262	0.200	0.176	0.512	0.029
I32	0.666	0.000	0.131	0.314	0.259	0.249	0.050	0.000
I41	0.666	0.000	0.136	0.340	0.293	0.183	0.058	0.000
I42	0.333	0.000	0.186	0.225	0.229	0.247	0.103	0.010
I51	0.233	0.000	0.080	0.340	0.40	0.180	0.000	0.000
I52	0.155	0.000	0.000	0.100	0.460	0.140	0.260	0.040
I53	0.190	0.000	0.182	0.201	0.391	0.214	0.009	0.000
I54	0.185	0.000	0.002	0.190	0.221	0.491	0.066	0.000
I55	0.113	0.200	0.200	0.150	0.449	0.000	0.000	0.000
I96	0.116	0.000	0.140	0.426	0.426	0.000	0.000	0.000
I61	0.327	0.036	0.258	0.366	0.263	0.070	0.012	0.000
I62	0.155	0.000	0.000	0.100	0.460	0.140	0.260	0.040
I63	0.190	0.000	0.182	0.201	0.391	0.214	0.009	0.000

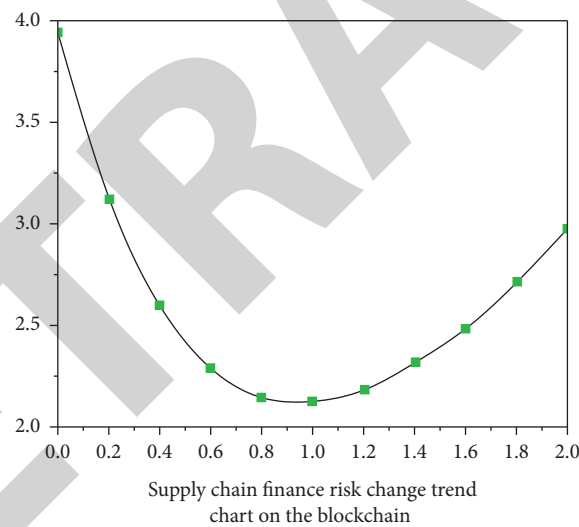Supply chain finance risk change trend
chart on the blockchain

Figure 12: Change trend of supply chain financial risk on the blockchain.

Table 12: Macro and industrial risk trends.

Time	0/8 months	1/8 months	2/8 months	3/8 months	4/8 months	5/8 months	6/8 months	7/8 months	8/8 months
Value at risk	5.780	5.820	5.840	5.866	5.980	5.920	5.940	5.966	5.966
Decrease value	−0.113	−0.114	−0.115	−0.115	−0.114	−0.115	−0.115	−0.115	−0.115
Impact value	0.437	0.349	0.320	0.332	0.436	0.539	0.451	0.343	0.368

Since there are too many three-level indicators, they will not be listed one by one here.

5.4.3. *Analysis of Simulation Operation Results.* In terms of the change curve of supply chain financial risk level on the block, it can be seen from Figure 12 and Table 12 that the supply financial risk on the block chain first decreases significantly and then increases slowly [22].

From the change of macro and industrial risk level, it can be seen that the macro and industrial risk value increases slowly with time, as shown in Figure 13.

In terms of the change in the credit risk level, the credit risk decreases with the growth of time, because in the long-
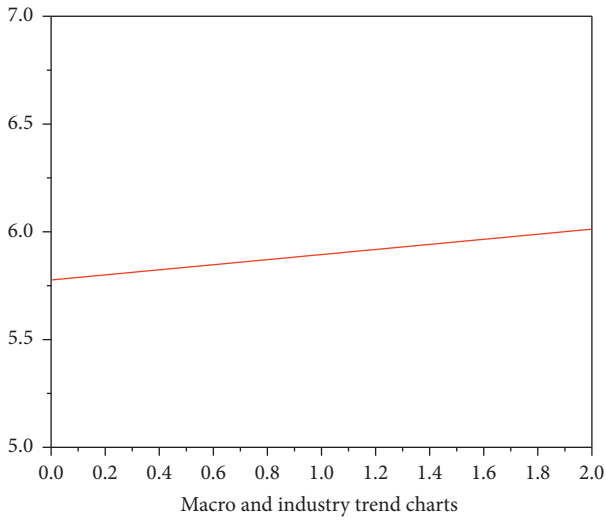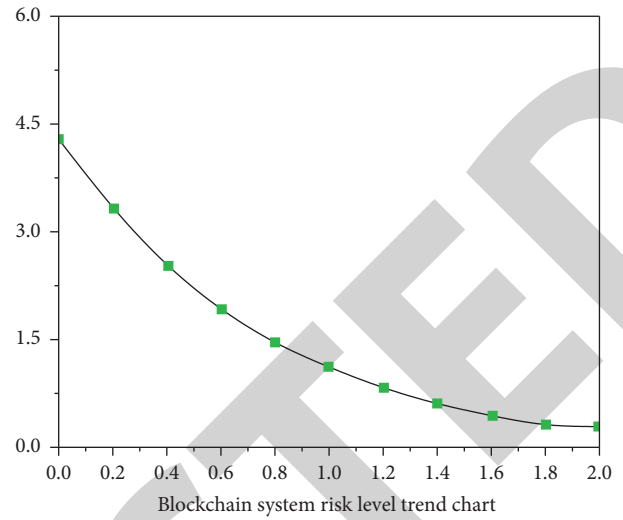
Figure 13: Macro and industry change trend.

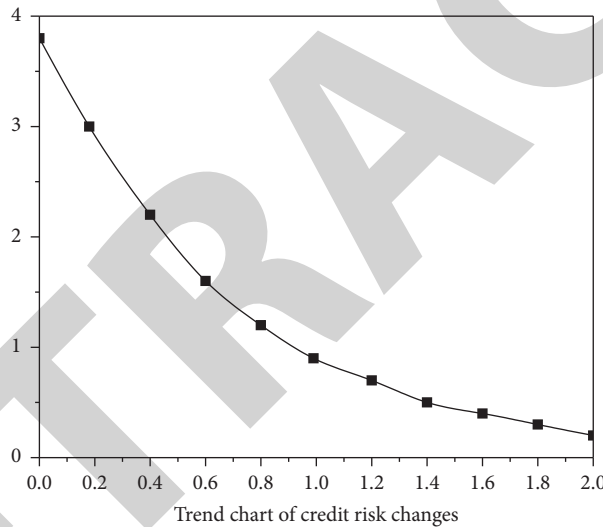Figure 15: Risk level trend of the blockchain system.

Figure 14: Change trend of credit risk.

Table 13: Change trend of credit risk.

Time	0/8 months	1/8 months	2/8 months	3/8 months	4/8 months	5/8 months	6/8 months	7/8 months	8/8 months
Value at risk	3.670	2.615	1.853	1.037	0.917	0.655	0.455	0.332	0.228
Decrease value	4.218	3.059	2.186	1.546	1.089	0.767	0.538	0.377	0.266
Impact value	1.101	0.785	0.555	0.392	0.278	0.194	0.146	0.088	0.077

term cooperation, the credit score of all parties in the blockchain will be higher and higher, and the credit risk will be lower and lower [23], as shown in Figures 14 and 15 and Table 13.

After obtaining the above results and changing the initial of each parameter, it is found that the obtained graph has no change in the trend, and the original or upward or downward trend of each risk has not changed. Macro and industry risks: the performance of macro and industrial risks is relatively gentle because the simulation period is two months and the time is relatively short. In such a short time, the possibility of drastic changes in the macro environment is less. As reflected in the system risk, the fluctuation range of macro and industrial risks is less. Credit risks: the credit risk decreases rapidly with the passage of time because the credit transmission function of the blockchain system greatly reduces the credit uncertainty. The relevant algorithms and unique mechanisms of the blockchain minimize the credit problems in the financing process, thus reducing the credit risk; Supply chain relationship risk [24]: it can be seen that the relationship risk of the supply chain also decreases rapidly, because with the continuous occurrence of

transactions, the reliability of the blockchain system ensures the reliability of transactions between the trading partners, making the relationship between the partners in the supply chain more reliable, thus reducing the relationship risks accordingly. Risk of pledge: the information of the blockchain is traceable, so that the cargo information and historical information can be queried conveniently and quickly, ensuring the accuracy of the pledge information and reducing the risk of the pledge; Operational risk level: The rise in the operational risk level is due to the lack of knowledge in people who do not fully understand the concept of blockchain, the lack of professionals, and the lack of relevant personnel training in enterprises. Over time, the number of operational errors will increase, resulting in an increase in operational risk; Blockchain system risk [25]: the risk reduction of the blockchain system is due to the continuous development and maturity of blockchain technology, and its own algorithm and mechanism are relatively mature, which ensures the reliability of the system. Therefore, the risk will be gradually reduced with the growth of time.

6. Conclusion

The addition of blockchain technology to the product market not only affects the scope of analytical measurement of key financial risk management products but also the impact on the value of instruments identified in the market. The integration of blockchain technology will change the measurement value of the key symbols. It has always been possible to introduce product sector blockchain to improve the timing of the industrial development, reduce the overall operating costs of the network, improve the investment capacity of the chain, and improve the operation of the financial network to meet the need for efficient technology and to be aware of the new developments in the financial equipment. This paper is intended to provide a comprehensive set of measurement measures for financial risk management chain in blockchain technology and leads to the following studies:

(1) The common behaviors of participants in supply chain finance under various financing modes are analyzed. Combined with the 5C factor analysis method, supply chain risk evaluation system and the operational risk measurement theory, the supply chain financial risk on the blockchain is identified, and the unique risk points of the supply chain system on the blockchain are effectively identified.

(2) According to the weight of each level of financial indicators in the block chain, the weight of each level of financial indicators is calculated by using the fuzzy evaluation method, and the final value of each level of financial indicators is calculated according to the weight of each level of financial indicators.

(3) Using system dynamics, this paper makes a detailed analysis of each subsystem of supply chain financial risk on the blockchain, draws the causality diagram and flow diagram of each subsystem, and explores the risk change trend of each subsystem and the change trend of the total risk system with time, so as to provide the basis of risk control for the introduction of blockchain technology in the supply chain financial industry.

Data Availability

The labeled data set used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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