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Service risk of energy industry international trade supply chain based on artificial intelligence algorithm

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A R T I C L E I N F O

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A B S T R A C T

With the deepening of the process of global economic integration, international trade supply chain financial services have also flourished. International trade supply chain financial services have played an important role in solving supply chain enterprise financing. As far as the energy industry is concerned, international trade supply chain financial services can provide sufficient credit support for energy companies. This solves the financing dilemma of small and medium-sized energy companies in import and export trade, and can also improve the capital turnover rate of large energy companies. However, because the international trade supply chain financial service still faces the influence of risks such as corporate credit risk, bank operational risk, and supply chain enterprise information transmission risk, its function of providing financing has not been fully exerted. Early warning and control of risks existing in international trade supply chain financial services can fully play the role of international trade supply chain financial services in promoting the development of the energy industry. Therefore, this article used three artificial intelligence (AI) algorithms, including artificial neural network, genetic algorithm and particle swarm algorithm, to analyze the risk of financial services in the international trade supply chain of the energy industry. A risk early-warning model about the financial services of the international trade supply chain of the energy industry was constructed, and an experimental study on the risk early-warning model was carried out. Research showed that the risk early warning model based on AI algorithm enabled banks to improve the accuracy of corporate credit assessment by 7.43% and the accuracy of information collection by 5.61%. It improved the forecast accuracy of external environmental risks by 3.52%, and reduced bank operational risk by 6.58% and legal and regulatory risk by 7.06%.

1. Introduction

The risk factors in international trade supply chain financial services limit the function of international trade supply chain financial services. The use of the risk early warning model based on artificial intelligence algorithm to analyze and warn the financial service risk of the international trade supply chain of the energy industry can solve the financing dilemma of energy small and medium-sized enterprises and help energy small and medium-sized enterprises expand their export scale. It can also help large energy companies reduce costs and enhance the competitiveness of energy companies. Therefore, the research in this paper is very necessary.

In order to promote the development of import and export trade, many scholars have studied the risks of financial services in the international trade supply chain. Wei Y Y analyzed the risks of international trade supply chain financial services from the perspective of commercial banks. He believed that the risks faced by banks should be managed and controlled, so as to promote banks to provide better financial service support (Wei, 2019). Chen S believed that international trade supply chain financial services have four risk factors: credit risk, cash flow risk, collateral risk and external environmental risk. Through the analysis of four risk factors, he proposed solutions such as strengthening the investigation of enterprise credit, implementing a multi-party risk-taking system, as well as improving collateral supervision and management (Chen, 2018). Yang W Q analyzed the risks faced by large and medium-sized foreign trade enterprises in developing supply chain trade financing business, and put forward suggestions on strengthening risk control and improving risk supervision mechanisms (Yang, 2019). Zhu Y Q studied the risk factors and their interaction in supply chain node enterprises, legal representatives, environmental resources and trade links, and provided support for the risk prediction and management of supply chain financial services (Zhu et al., 2018). Song C constructed an evaluation system of supply chain financial service

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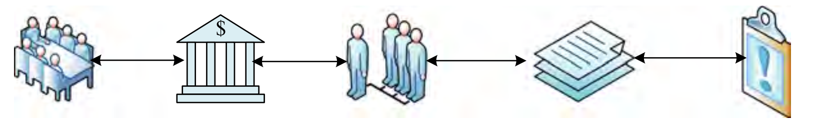


Fig. 1. Risk factors for supply chain financial services.

risk by analyzing the supply chain financial service risk (Song, 2020). In order to solve the financing problem of small and medium-sized enterprises, Wang Y M established a supply chain financial risk early warning system applied to SME financing services (Wang, 2017). Chen L proposed four countermeasures for international trade supply chain financial financing, including establishing a supply chain financial risk identification and early warning system (Chen, 2022). Although there are many studies on the risk of financial services in the international trade supply chain, few are applied to the energy industry.

With the rapid development of computer technology, the application fields of AI algorithms are becoming more and more extensive. Peng K H used AI algorithm to establish the index system of test paper, which improved the efficiency of automatic test group (Peng et al., 2018). Zhang W studied the application of AI algorithm in image processing, and constructed an image processing system based on AI algorithm (Zhang, 2018). Bao T applied AI algorithm to the research of power grid, and designed reactive power optimization analysis software based on AI algorithm (Bao et al., 2018). Zhou Y Y discussed the application of AI algorithms in acupuncture research, and established an evaluation mechanism for acupuncture efficacy using AI algorithms (Zhou et al., 2021). Yang F built a prediction model of catalytically cracked gasoline yield based on AI algorithm, which further improved the economic benefits of petrochemical enterprises (Yang et al., 2019). Gao Y used AI algorithm to study the diagnosis and prediction of venous thrombo-embolism (VTE), and established a VTE risk prediction model based on AI algorithm (Gao et al., 2021). When Li X studied the security of wireless mobile communication, he used AI algorithm to construct a risk assessment model for wireless mobile communication (Li, 2020). Although the application fields of AI algorithms are relatively wide, there are few related researches on the risk analysis of financial services in the international trade supply chain of the energy industry.

In order to solve the financing difficulties of small and medium-sized energy enterprises and improve the turnover rate of large enterprises, this paper proposed a risk early warning model for financial services in the international trade supply chain of the energy industry based on AI algorithms. In this way, the role of international trade supply chain financial services in promoting the development of the energy industry can be better played, and the development of import and export trade can be promoted.

2. Risk warning model of supply chain financial services based on AI algorithm

(1) Risk factors of supply chain financial services

International trade supply chain financial services refer to the financing and wealth management services provided by banks to enterprises in international trade (Sornalakshmi et al., 2022). The risk factors of the international trade supply chain financial services in the energy industry are summarized, and four basic factors are extracted through literature research. The four basic factors are analyzed in detail, as shown in Fig. 1.

It can be seen from Fig. 1, the risks of financial services in the international trade supply chain of the energy industry mainly include five aspects: credit risk of energy companies, bank operational risk, information communication risk, legal and regulatory risk, and external environmental risk. The connotation of the credit risk of energy companies has two aspects, one is the credit risk of large energy companies, and the other is the credit risk of small and medium energy companies. If large-scale energy companies are eager for quick success, they only pay attention to their immediate interests, and use their trade advantages to suppress the price costs of small and medium-sized energy companies and squeeze the living space of small and medium-sized energy companies. It may cause the debt of small and medium-sized energy companies to exceed their own limits, thereby affecting the stability of the entire supply chain. The credit risk of small and medium-sized energy companies refers to the fact that small and medium-sized energy companies are not as large as large energy companies. The credit evaluation of small and medium-sized energy companies is often more stringent, and the credit expectations of small and medium-sized energy companies are relatively conservative. In addition, since there are more small and medium-sized energy companies than large energy companies, banks may not conduct credit investigations on small and medium-sized energy companies very comprehensively, and credit investigations on foreign energy industry supply chains are more one-sided. Bank operation risk refers to the risk brought by the bank's non-standard or illegal operation in the operation links such as credit investigation, service plan design, financing approval and so on. For example, when an energy company conducts financing approval, the employee makes mistakes or illegal operations increase the amount of financing. The risk of information transmission means that if an error occurs in the transmission of information in the supply chain, it would affect the bank's information collection and management, and then directly affect the enterprise's financing approval. Legal and regulatory risks refer to the fact that due to different laws in different countries, some companies would take advantage of legal loopholes to seek benefits and defraud supply chain financial services. External environmental risk refers to the risks caused by the international market environment to supply chain financial services, including political environment, corporate operating policies, and economic stability.

(2) Risk countermeasures for supply chain financial services

Effective prevention and control of supply chain financial service risks in international trade is conducive to creating a favorable environment for the development of import and export enterprises and promoting economic development (Leukel and Sugumaran, 2022). In order to promote the development of the energy industry, some measures are put forward for the energy industry to deal with the risks of supply chain financial services in international trade, as shown in Fig. 2.

It can be seen from Fig. 2, the main measures to deal with the risks of supply chain financial services are: the strictness of enterprise access standards, the establishment of an intensive operation platform, the establishment of a joint credit system, the use of credit bundling, the rational use of laws and regulations,

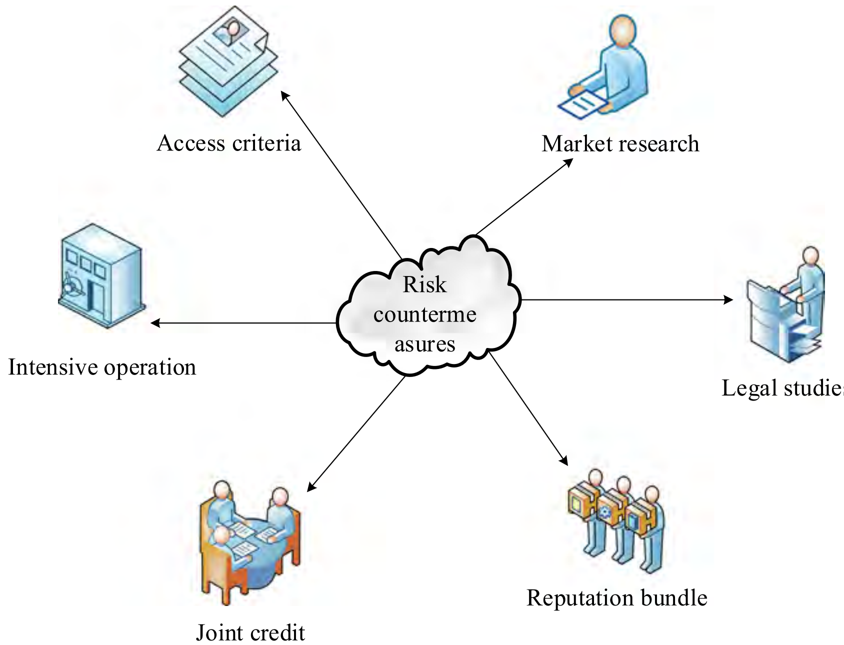


Fig. 2. Risk countermeasures for supply chain financial services.

the rational application of laws and regulations, and the strengthening of market information research. The strictness of enterprise access standards means that banks, as providers of supply chain financial services, should conduct access assessments for supply chain enterprises. It is necessary to select enterprises with stable operation status and real business background to provide financing services. The establishment of an intensive operation platform means that the bank can change the previous credit management strategy and develop an intensive operation platform by establishing an information exchange platform with the enterprise, so as to realize the effective monitoring of the capital flow and cash flow of the enterprise. The establishment of the joint credit system means that the credit status of the entire supply chain enterprises should be considered, rather than just the credit of large enterprises. The adoption of the credit bundling method refers to bundling the credit assets of the financing company with the financing projects, and introducing a third-party institution to diversify the credit risk of the company. The rational application of laws and regulations means that banks should carefully study the legal provisions of the location of the financing enterprise and study the application of financing products. A legal affairs department should be established to deal with various legal issues by strengthening cooperation with law firms, so as to protect the financing security of banks. The strengthening of market information research means that banks should invest a lot of human resources and technical resources to investigate and analyze market information, and use the survey results to formulate reasonable credit policies.

(3) Architecture of supply chain financial service risk early warning model

The establishment of supply chain financial service risk early warning model is of great significance for predicting and reducing supply chain financing risks (Wang et al., 2022). By analyzing the risk factors and risk response measures of supply chain financial services, AI algorithms and some network devices are used to establish a risk early warning model, as shown in Fig. 3.

It can be seen from Fig. 3, the AI algorithm-based supply chain financial service risk early warning model is divided into three modules: risk data collection, risk early warning calculation, and risk event summary. Risk data collection consists of managers, monitoring systems, and external data collection systems. Managers should not only use the monitoring system to monitor the supply chain financial service risks of their own companies, but also use the data collection system to collect and analyze the external supply chain financial service risks. The calculation of risk early warning relies on AI algorithms and computer technology, and the corresponding risk index is calculated according to the set risk standards. After the calculation results come out, the warning information would be issued according to the corresponding procedures, so that supply chain enterprises or banks can quickly take measures to deal with the risks of supply chain financial services. After this financing risk event is resolved, senior personnel of supply chain enterprises or banks would hold a meeting to summarize the problems existing in the risk pre-control of supply chain financial services. The effectiveness of response measures is also evaluated, and questions and comments are recorded in a database.

3. Application of AI algorithm in risk assessment of supply chain financial services

(1) Artificial neural network

Artificial neural network is a nonlinear and adaptive information processing system composed of a large number of interconnected processing units, which has four characteristics of nonlinearity, non-limitation, very qualitative and non-convexity (Sankar et al., 2022).

The risk factors affecting supply chain financial services are set as independent variable χ, and the degree of risk change is set as γ, there have:

$$\chi = (\chi_1, \chi_2, \ldots, \chi_i) \tag{1}$$

$$\gamma = \left(\gamma_1, \gamma_2, \ldots, \gamma_j\right) \tag{2}$$

It is supposed the control point of the universe is χ_p $(p = 1, 2, \Lambda, i)$; γ_q $(q = 1, 2, \Lambda, j)$.

It is assumed that the step size is $\Delta_1 = \chi_{p+1} - \chi_p > 0$, $\Delta_2 = \gamma_{q+1} - \gamma_q > 0$, then there have:

$$\omega_{s,t} = (1 - |\chi - \chi_s| / \Delta_1)(1 - |\gamma - \gamma_t| / \Delta_2) \tag{3}$$

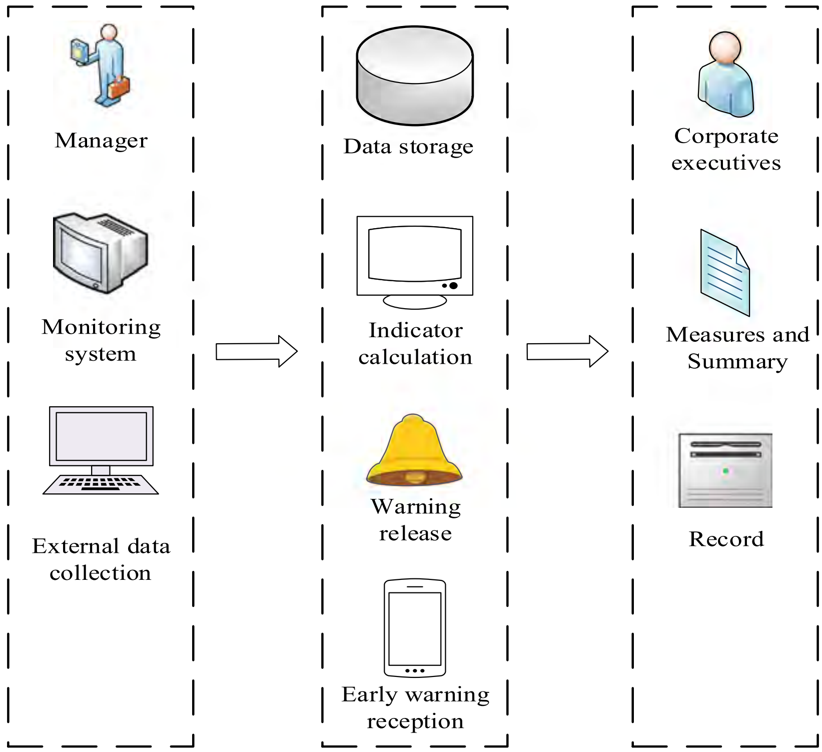


Fig. 3. Architecture of supply chain financial service risk early warning model.

It is assumed that risk factor data (χ, γ) have l groups, then there is matrix λ as:

$$\lambda = \sum_{c=1}^{l} \lambda_{pq}^{c}, p = 1, 2, \ldots, i; q = 1, 2, \ldots, j \tag{4}$$

The expression of fuzzy matrix R is:

$$R = \lambda / l_{pq}, p = 1, 2, \ldots, i; q = 1, 2, \ldots, j \tag{5}$$

Among them, $l_{pq} = \max(\lambda)$, and $0 \leq R \leq 1$.

It is assumed that $Y^{(1)}, X^{(1)}$ is a fuzzy subset of domains χ, γ, there are:

$$Y^{(1)} = X^{(1)} * R \tag{6}$$

Among them, "*" represents the fuzzy relation matrix operation rule.

When $\chi \leq \chi_1$, there are:

$$X^{(1)} = [1, 0, 0, \Lambda, 0] \tag{7}$$

When $\chi > \chi_i$, there are:

$$X^{(1)} = [0, 0, 0, \Lambda, 1] \tag{8}$$

When $\chi_1 < \chi < \chi_i$, there are:

$$X^{(1)} = \left\lfloor \max\left(0, 1 - \left|\chi - \chi_q\right| / \Delta_1 - \Delta_2\right) \right\rfloor \tag{9}$$

(2) Genetic algorithm

Genetic algorithm uses computer technology and mathematical thinking to simulate the natural evolutionary process. It finds the optimal solution by transforming the process of solving problems in other fields into processes such as chromosome crossover and mutation in the biological field (Yildirim and Cengiz, 2022).

After extracting and combining the risk features of supply chain financial services, the final feature vector is obtained as:

$$H(J, I) = \sum_{p=1}^{c} g_p \sqrt{\left(f_{Jp} - f_{Ip}\right)^2} \tag{10}$$

Among them, J is the example risk and I is the main preventive risk. c is the number of features, and g_p is the weight.

The optimal weight of supply chain financial service risk identification and classification is:

$$D = f(G) = \sum_{p=1}^{c} \sqrt{AP} \tag{11}$$

Among them, D is the optimal weight in g_p, and $\sqrt{AP}$ is the accuracy and precision.

The genetic algorithm of characteristic weight value is used to optimize the risk warning model of supply chain financial services, then the weight update formulas are:

$$G^{(s)} = G^{(s-1)} - \beta \frac{gQ(v, \omega, \lambda)}{\kappa G} \Big|_{G=G^{(s-1)}} \tag{12}$$

$$\omega^{(s)} = \omega^{(s-1)} - \beta \frac{\kappa Q(v, \omega, \lambda)}{\kappa \omega} \Big|_{\omega=\omega^{(s-1)}} \tag{13}$$

$$\lambda^{(s)} = \lambda^{(s-1)} - \beta \frac{\kappa Q(v, \omega, \lambda)}{\kappa \lambda} \Big|_{\lambda=\lambda^{(s-1)}} \tag{14}$$

Among them, G is the quantitative weight of the optimized supply chain financial service risk. ω is the bias value and λ is the weight parameter.

(3) Particle swarm algorithm

Particle swarm optimization is a random search algorithm that finds the optimal solution by imitating the group behavior of birds (Hoettecke et al., 2022).

It is assumed that the current position of particle p is ω, and the optimal position that particle p has experienced is ν, then there are:

$$\omega_p = \left(\omega_{p1}, \omega_{p2}, \Lambda, \omega_{pm}\right) \tag{15}$$

$$\nu_p = \left(\nu_{p1}, \nu_{p2}, \Lambda, \nu_{pm}\right) \tag{16}$$

The optimal position of particle p is determined as:

$$\nu_p(j+1) = \begin{cases} \nu_p(j), f\left(\omega_p(j+1)\right) \geq f\left(\nu_p(j)\right) \\ \omega_p(j+1), f\left(\omega_p(j+1)\right) < f\left(\nu_p(j)\right) \end{cases} \tag{17}$$

If the total number of swarm particles is i, the best position experienced by all particles is:

$$\nu_l(j) \in \{\nu_0(j), \nu_1(j), \Lambda, \nu_i(j)\} \lfloor f(\nu_l(j)) = \min\{f(\nu_0(j)), f(\nu_1(j)), \Lambda, f(\nu_i(j))\} \tag{18}$$

The evolution function of particle swarm optimization can be described as:

$$\beta_{pq}(j+1) = \beta_{pq}(j) + k_1 g_1(j) \lfloor \nu_{pq}(j) - \omega_{pq}(j) \rfloor + k_2 g_2(j) \lfloor \nu_{lq}(j) - \omega_{pq}(j) \rfloor \tag{19}$$

$$\omega_{pq}(j+1) = \omega_{pq}(j) + \beta_{pq}(j+1) \tag{20}$$

Among them, q represents the dimension of particle p, and j represents the number of iterations. k_1, k_2 are acceleration constants, and g_1, g_2 are independent random functions.

4. Experimental purpose and design of risk early warning model

(1) Experimental purpose

By using artificial neural network, genetic algorithm and particle swarm algorithm to conduct experimental research on supply chain financial service risk, it is proved that the risk early warning model constructed in this paper can reduce the supply chain financial service risk faced by the energy industry in international trade, thereby promoting the development of the energy industry.

(2) Experimental design

4 banks were selected and they were divided into two groups. The first group used the AI algorithm-based risk early-warning model to warn and control the risks of supply chain financial services. This group was called Group R, which included Bank S and Bank T. The second group used traditional risk early-warning methods to pre-warn and control the risks of supply chain financial services. This group was called Group U, which included Bank V and Bank W. A 6-month experimental study was conducted on 4 banks, and the experimental study was carried out from five aspects: assessing the accuracy of corporate credit, the incidence of operational risk, the accuracy of information collection, the degree of changes in legal and regulatory risks, and the accuracy of external environmental risk prediction. After the experiment is over, the experimental results are observed and analyzed.

5. Experimental results of the risk early warning model

(1) Evaluation of enterprise credit accuracy

A 6-month corporate credit assessment test was conducted for Group R banks and Group U banks. Group R banks used the AI algorithm-based risk early warning model for evaluation and testing, while Group U banks used traditional risk early warning methods for evaluation and testing. Data statistics were carried out once a month to obtain the accuracy of the bank's credit evaluation of the enterprise, as shown in Fig. 4.

Fig. 4a shows the bank's assessment accuracy of corporate credit, and Fig. 4b shows the bank's average assessment accuracy of corporate credit. On the whole, the evaluation accuracy of Bank S and Bank T was higher than that of Bank V and Bank W. The evaluation accuracy of Bank S in the first month was 73.66%, Bank T was 72.7%, Bank V and Bank W were 65.7% and 64.8%, respectively. In the first month, the evaluation accuracy of Group R banks was 7.93% higher than that of Group U banks. The risk early warning model based on AI algorithm played a role in improving the accuracy of bank evaluation from the very beginning. From the final test results, the evaluation accuracy of Bank S and Bank T were 85.26% and 85.39%, respectively, and the evaluation accuracy of Bank V and Bank W were 79.63% and 81.59%, respectively. The evaluation accuracy of the Group R was higher than that of the Group U. In the fourth month, Bank V and Bank W both experienced a small decrease in the evaluation accuracy, while Bank S and Bank T did not show a downward trend, indicating that the AI algorithm-based risk early warning model is relatively stable in terms of evaluation accuracy. The average evaluation accuracy of the Group R was 79.81%, and that of the Group U was 74.29%. The average evaluation accuracy of the Group R was 7.43% higher than that of the Group U, which indicated that the risk early warning model based on AI algorithm can play a significant role in improving the accuracy of assessment.

Table 1
The bank's average operational risk rate.

	Bank S	Bank T	Bank V	Bank W
Service plan design	22.56%	21.63%	23.36%	24.47%
Financing approval	23.28%	21.24%	23.69%	24.13%
Loan	21.29%	20.23%	21.87%	22.47%
Post-credit management	23.69%	22.16%	24.56%	23.97%

(2) Incidence of bank operational risk

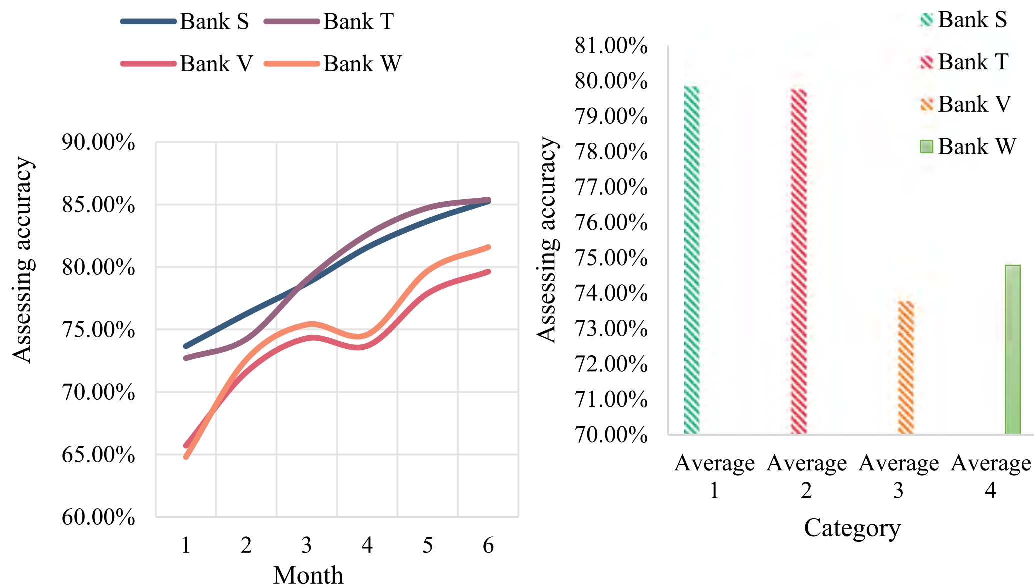
A 6-month study on the incidence of bank operational risk was conducted to compare the differences between the R group banks and the U group banks. The experimental results are shown in Table 1.

It can be seen from Table 1, the incidence of bank operational risk was reflected in the four operational links of service plan design, financing approval, lending and post-credit management. In the service plan design, Bank T had the lowest incidence of operational risk, 21.63%, and Bank W had the highest incidence of operational risk, 24.47%. In the process of financing approval, Bank T had the lowest operational risk incidence rate of 21.24%, and Bank S had an operational risk incidence rate that was 0.41% lower than that of Bank V. In the lending process, the operational risk rate of Bank T was 20.23%, which was 2.24% less than that of Bank W. In terms of post-credit management, Bank V had the highest incidence of operational risk at 24.56%, which was 2.4% higher than that of Bank T. The overall operational risk incidence rates of Bank S and Bank T were 22.71% and 21.32%, respectively. The overall operational risk incidence rates of Bank V and Bank W were 23.37% and 23.76%, respectively. The incidence of operational risk in Group R was 6.58% lower than that in Group U. Risk early warning models based on AI algorithms played an important role in reducing the incidence of bank operational risks.

(3) Accuracy of information collection

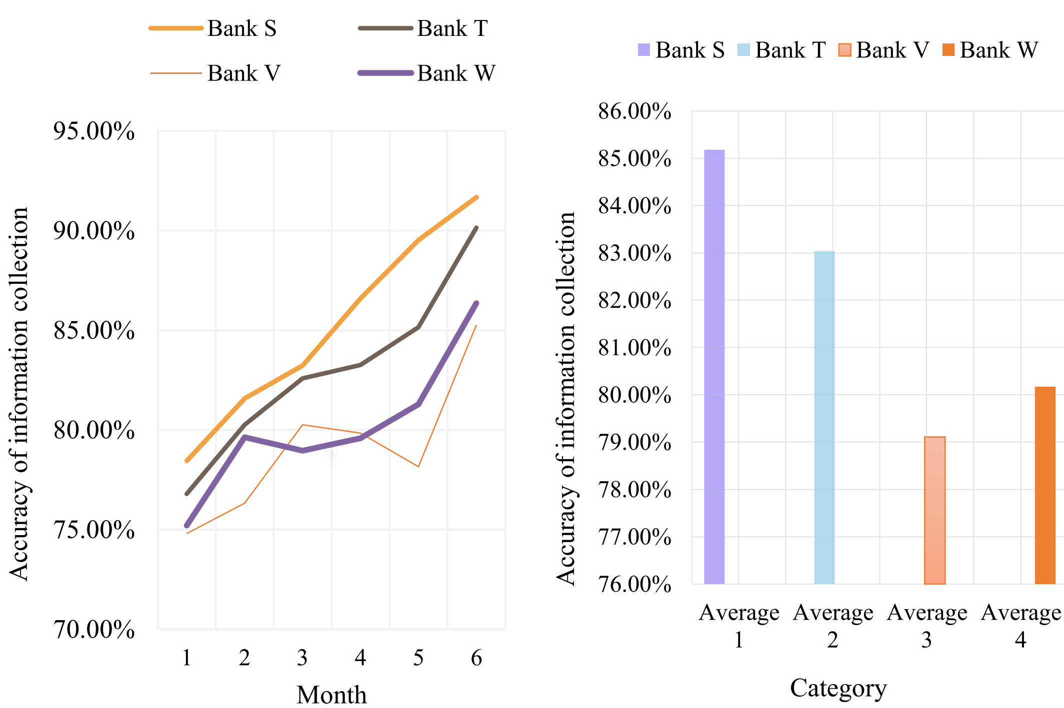
A 6-month survey was conducted on the accuracy of information collection by banks. By comparing the differences between the Group R banks and the Group U banks, the effect of the risk early warning model and the traditional risk early warning method on the accuracy of information collection was studied. The specific content is shown in Fig. 5.

Fig. 5a shows the information collection accuracy of banks, and Fig. 5b shows the average information collection accuracy of banks. It can be seen from Fig. 5a, the information collection accuracy of the two banks in the Group R was in a steady upward trend, and the development trend of the information collection accuracy of the two banks in the Group U had risen and fallen, which is not stable enough. In the fourth month, Bank V's information collection accuracy decreased by 0.41% compared with the third month, and decreased by 1.69% in the fifth month. Bank W's information collection accuracy dropped by 0.67% in the third month. It showed that compared with the traditional risk early warning method, the risk early warning model based on AI algorithm had the advantage of stability in improving the accuracy of information collection. In the sixth month, the accuracy of information collection of banks in Group R reached 90.91%, and



a. Bank assessment accuracy **b.** Bank's average assessment accuracy

Fig. 4. Assess corporate credit accuracy.



a. Accuracy of information collection by banks **b.** Average Information Gathering Accuracy of Banks

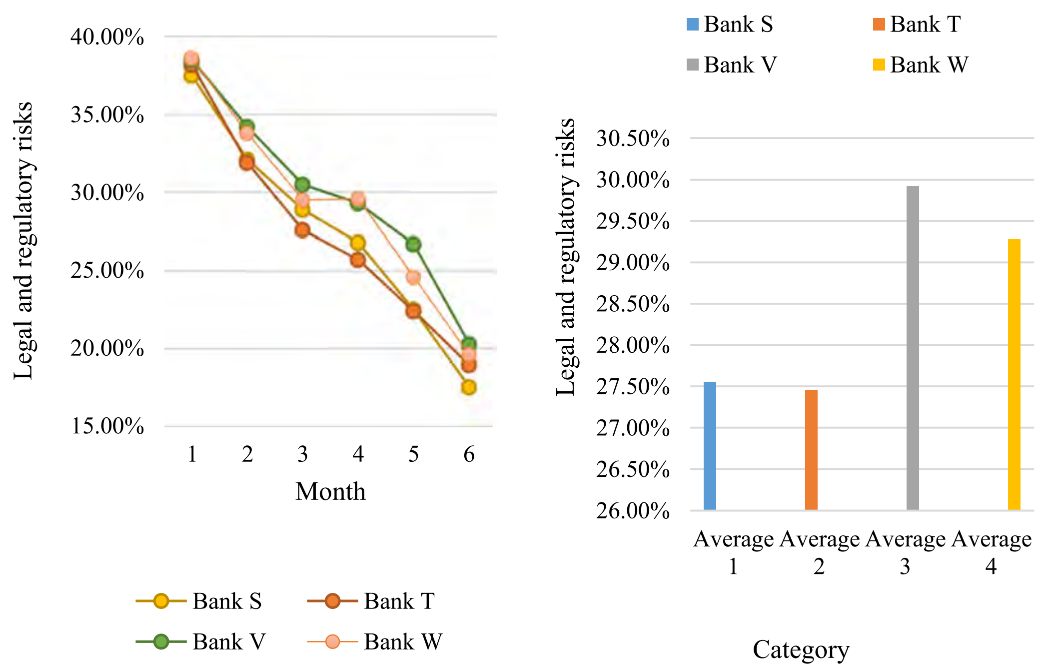
Fig. 5. Information communication risks.

the accuracy of information collection of banks in Group U was 85.81%. In terms of the final improvement effect of the accuracy of information collection, the risk early warning model based on the AI algorithm performed relatively well. The average information collection accuracy of the Group R was 84.11%, and that of the Group U was 79.64%. The average information collection accuracy of the Group R was 5.61% higher than that of the Group U.

(4) Changes in the risk of laws and regulations

The Group R banks using the risk early warning model and the Group U banks using the traditional risk early warning method were tested for their performance in reducing legal and regulatory risks, and were recorded once a month. The results are shown in Fig. 6.

Fig. 6a shows the legal and regulatory risk indicators faced by banks when providing financing services, and Fig. 6b is the average legal and regulatory risk indicators faced by banks during



a. Legal and regulatory risks faced by banks **b.** Average legal and regulatory risk indicators

Fig. 6. Legal and regulatory risks.

a 6-month period. On the whole, the legal and regulatory risk indicators of Group R and Group U were in a downward trend, and the degree of change was more obvious. The legal and regulatory risk indicators of the four banks had dropped from more than 30% to less than 21%, indicating that the early warning and control of legal and regulatory risks were effective. The risk index of laws and regulations of Bank S in the first month was 37.5%, and the risk index in the second month decreased by 5.4%, and the degree of decline was more obvious. The legal and regulatory risk index of Bank T in the first month was 38.5%, and the risk index in the second month decreased by 6.3%, and the decline rate was also faster. In the sixth month, the legal and regulatory risk indicators of Bank S and Bank T were 17.53% and 18.95% respectively, which indicated that the AI algorithm-based risk early warning model plays a more prominent role in reducing legal and regulatory risks. The legal and regulatory risk indicators of Bank V and Bank W also decreased to a large extent in the sixth month, but the legal and regulatory risk indicator of Bank V decreased by only 1.2% in the fourth month. The legal and regulatory risk index of Bank W increased by 0.1% in the fourth month, and the traditional risk early warning method was not stable enough in reducing legal and regulatory risks. The average legal and regulatory risk index was 27.51% in the R group and 29.6% in the Group U. The average legal and regulatory risk index of the Group R was reduced by 7.06% compared with the Group U.

(5) Accuracy of external environmental risk prediction

Environmental changes in the international market would increase the operational risks of supply chain companies. For the safety of their own funds, banks should pay close attention to the operating environment of the international market when providing financing services. A 6-month study was conducted on the accuracy of the bank's external environmental risk prediction, as shown in Fig. 7.

Fig. 7a shows the bank's external environmental risk prediction accuracy, and Fig. 7b shows the bank's average external environmental risk prediction accuracy. The accuracy of the external environmental risk forecast of Bank S in the first month was 75.68%, which increased by 2.01% in the second month, and has maintained a relatively stable growth trend since then. In the sixth month, the risk prediction accuracy reached 82.56%, which was 6.88% higher than that in the first month. The development trend of the forecast accuracy of Bank T was roughly the same as that of Bank S, and it had always maintained an upward trend. In the sixth month, the risk prediction accuracy of Bank T reached 82.33%, which was 6.08% higher than that in the first month. The prediction accuracy of Bank V in the fourth month decreased by 0.25% compared to the third month, and the risk prediction accuracy in the sixth month was 78.74%. In the fifth and sixth months, the risk prediction accuracy of Bank W declined. In the sixth month, the risk prediction accuracy was 77.59%. The external environmental risk prediction accuracy of the Group R was 79.34%, and that of the Group U was 76.64%. The external environmental risk prediction accuracy of the Group R was 3.52% higher than that of the Group U. In general, compared with traditional risk early warning methods, AI algorithm-based risk early warning models can not only play a role in improving the accuracy of external environmental risk forecasting, but also have stability when playing a role.

6. Conclusions

International trade supply chain financial services still face the impact of corporate credit risk, bank operational risk and other risks. Traditional risk early warning methods have limited early warning and prevention capabilities for supply chain financial service risks, resulting in insufficient functions of supply chain financial services. In order to solve this problem, three AI algorithms, artificial neural network, genetic algorithm and particle swarm algorithm, were used to analyze the financial service risk of the international trade supply chain of the energy industry. A risk early-warning model for the financial services of the international trade supply chain of the energy industry was constructed. Through experiments, it was proved that the risk early-warning model based on the AI algorithm can reduce the

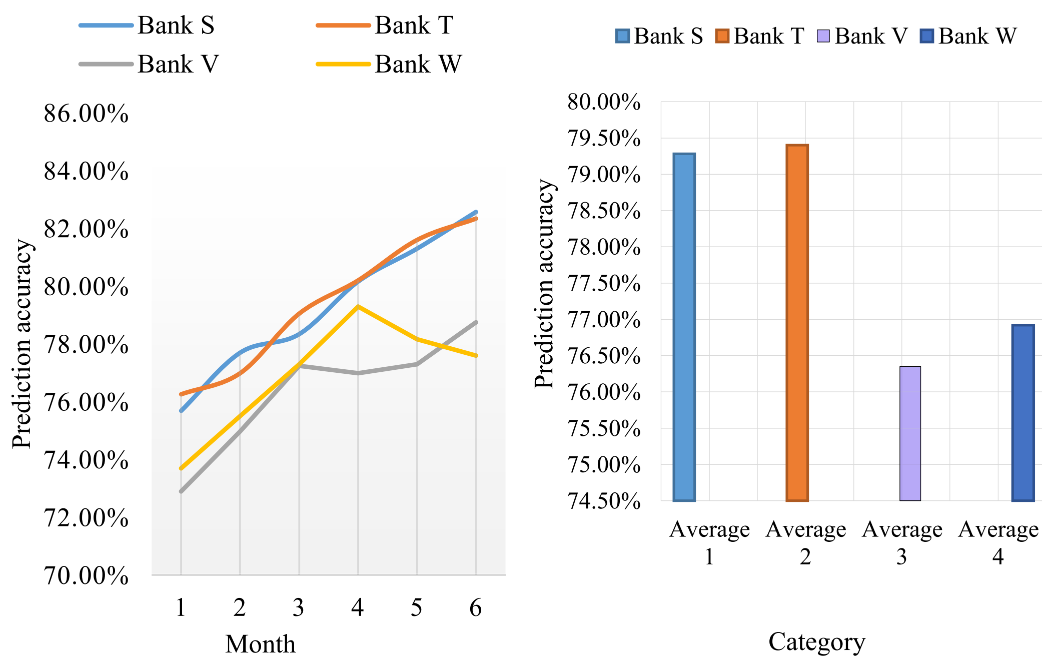


Fig. 7. External environmental risk prediction accuracy.

risks existing in the financial services of the international trade supply chain of the energy industry. The AI algorithm-based risk early warning model can help supply chain financial services play a more powerful role, thereby helping small and medium-sized energy companies to finance and expand the scale of imports and exports. It can also improve the capital turnover rate of large energy companies and reduce operating costs.

CRediT authorship contribution statement

Chang Liu: Conceptualization, Methodology, Data curation, Writing – original draft. **Shixin Yang:** Conceptualization, Methodology, Data curation, Writing – original draft. **Tianxu Hao:** Visualization, Investigation. **Ruijie Song:** Visualization, Investigation.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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