ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20230801000841
Original scientific paper

A Dynamic Credit Evaluation Approach Using Sensitivity-Optimized Weights for Supply Chain Finance

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Abstract: Supply chain financing provides important funding channels for micro and small enterprises (MSEs), but effectively evaluating their creditworthiness remains challenging. Past methods overly rely on static financial indicators and subjective judgment in determining credit evaluation weights. This study proposes a dynamic credit evaluation approach that uses sensitivity analysis to optimize the weighting scheme. An indicator system is constructed based on the unique characteristics of e-commerce MSEs. The weight optimization integrates subjective, objective, and sensitivity-based methods to reflect specific financing scenarios. A system dynamics model simulates the credit evaluation mechanism and identifies the sensitivity of each influencing factor. The resultant comprehensive weights are applied in a TOPSIS-GRA dynamic evaluation model to assess MSE credit levels over time. An empirical analysis of 20 online stores demonstrates the proposed model's advantages in accurately revealing credit rankings relative to conventional static models. This research provides an effective data-driven weighting technique and dynamic evaluation framework for supply chain finance credit assessment.

Keywords: e-commerce supply chain financing; dynamic credit evaluation; micro and small enterprises (MSEs); weight optimization

1 INTRODUCTION

Micro and small enterprises (MSEs), particularly those in developing economies, are engines of innovation, employment generation, and local economic development. Nevertheless, their constrained scale and resources render them susceptible to market fluctuations and hinder their access to conventional funding sources. In this context, supply chain financing emerges as a crucial lifeline for MSEs, affording them essential access to financial means necessary for their growth and sustainability.

However, MSEs often operate in highly dynamic and evolving sectors, such as e-commerce, where business models and market dynamics can swiftly transform. This dynamic environment demands an assessment framework that not only considers history ical financial performance but also accommodates the agility and adaptability of these enterprises in reacting to shifting market conditions. Past credit rating models face limitations in the weighting scheme and static evaluation approach [1, 2]: 1) Weights are overly based on subjective judgment versus data-driven methods. This risks inaccuracy and lack of specificity to the financing scenario. 2) The static evaluation cannot reveal credit trends over time or respond to data changes.

This study aims to address these gaps by proposing a dynamic credit evaluation approach that utilizes sensitivity analysis to optimize the weighting scheme. The specific contributions are: 1) Construct an indicator system based on e-commerce MSE characteristics. 2) Integrate subjective, objective, and sensitivity-based methods to determine scenario-specific weights. 3) Apply a system dynamics simulation to identify the sensitivity of each influencing factor. 4) Develop a TOPSIS-GRA dynamic evaluation model to assess credit levels temporally. 5) Empirically demonstrate the proposed model's ability to reveal credit rankings relative to conventional static models.

The paper is organized as follows. Section 2 is dedicated to the literature review.The indicator system, the weight optimization process, and TOPSIS-GRA Dynamic Credit Evaluation for MSEs are described in Section 3. The results and discussion are presented in Section 4 and Section 5 concludes.

2 LITERATURE REVIEW

2.1 Credit Evaluation Indicators and Systems

The process of determining the credit evaluation indicator system for MSEs is divided into three stages. The first is based only on the financial indicators of MSEs. The second is a comprehensive evaluation stage based on financial and non-financial indicators [3]. Complex changes in supply chain transactions have led to the third stage of multiagent credit evaluation, which further expands the scope of evaluation to the study of other relevant subjects and intersubject relationships [4]. Scholars have generally considered the factors influencing the credit levels of MSEs from three perspectives: enterprise characteristics [5], operating conditions [6], and industrial environment [7]. As it is difficult to obtain financial information for MSEs with low transparency, we posit that nonfinancial information indicators should be emphasized for credit evaluation.

2.2 Credit Evaluation Weighting Methods

Subjective, objective, and combination weighting methods are currently used for MSE credit evaluation indicators. Scholars have considered the allocation of expert weights at the indicator level or have made reasonable predictions for the ideal scheme through individual decision-making [8], thus determining the combined weight of the subjective weighting in the group. Objective weighting methods, such as the entropy weight method [9] and coefficient of variation (CV) method [10], determine the weight based on indicator data information. The combination weighting method integrating the two methods is also widely adopted [11]. Modified subjective G2 weighting based on the CV method can avoid the disadvantage of being unable to scientifically allocate the combined coefficients [12]. In addition, a sensitivity analysis based on the indicator system itself reflects the information content relative to the information sensitivity of the indicator [13]. In the dynamic credit evaluation process, time has a greater impact on the evaluation results. Recently, scholars have begun to explore dynamic credit evaluation systems based on time-sequence data [2], which provides new ideas for dynamic credit research.

2.3 Dynamic Credit Evaluation Models

Recently, researchers have been exploring a dynamic credit evaluation system based on time series data. For instance, Zhang [14] applied algorithms like SOM and K-means to the dynamic credit assessment and also introduced fuzzy cluster analysis to combine evaluation information more effectively [2]. Building on this work, a dynamic credit evaluation method called TOPSIS-GRA was developed. This method combines the traditional TOPSIS approach with grey relational analysis, and it takes into anti-risk rewards and penalties [15]. Some scholars have also made advancements in selecting data. The dynamic credit evaluation model enhances evaluation accuracy and addresses credit assessment errors [16]. Later researchers incorporated the concept of time weighting [17] to include time series data in credit research.

2.4 Research Gaps

Currently, the foundational research on credit evaluation is reaching maturity, yet there is inadequate attention given to the distinctiveness of the enterprise's financing environment in the following aspects: 1) Indicators are primarily chosen on the financial situation, with supplementary consideration of development prospects and relationships among financing entities. 2) Weight assignment relies mainly on subjective expert judgment, leading to a singular qualitative evaluation. 3) The concept of "dynamic" lacks comprehensive interpretation. Credit levels are predominantly measured using static weights, and a comprehensive dynamic evaluation system is yet to be established.

This study seeks to merge the conventional credit evaluation weighting approach with a realistic operational scenario designed for MSEs. This integration allows for the implementation of a scenario-based weighting methodology within an e-commerce context.

3 RESEARCH METHODOLOGY

3.1 Construction of a Credit Evaluation Indicator System

In contrast to traditional credit evaluations, e-commerce MSEs rely on online platforms, which are an important part of supply chain financing. MSEs with products with a certain market competitiveness can maintain the long-term operation of the supply chain. Therefore, we posit that the credit evaluation of MSEs in e-commerce should include a focus on the characteristics of the e-commerce supply chain [18]. In addition, as the level of risk is closely related to credit [19], we argue that credit evaluations should consider the ability to control risk. Finally, the inter-agent cooperation relationship should also be considered in the online supply chain.

The credit-influencing factors are based on a comprehensive analysis of the characteristics of MSEs in e-commerce and actual surveys, combined with the 4P classification of the marketing mix (i.e., product, price, place, and promotion) and the 5C analysis of marketing (i.e., company, collaborators, customers, competitors, and context) methods. It includes product situation, management level, and service level (Tab. 1).

Table 1 Main factors affecting the credit of micro and small enterprises (MSEs)

Level indicators	Secondary indicators	Index number	Interpretation	Authors
Product situation	Product quantity	A1	The comparative advantage of enterprises in product quantity can be transferred to the credit level channel.	Yan, Li, Gao, and Wu [20]
	Product quality	A2	There is a significant positive impact between product quality and enterprise credit.	Liu and Feng [21]
	Product sales volume	A3	The overall strength and product quality level of the enterprise.	Kouvelis and Zhao [22]
	Product pricing	A4	The more stable the product pricing, the higher the credit level of the enterprise.	Kouvelis and Zhao [22]
	Product disclosure	A5	The more complete the product information disclosure, the higher the credit level of the enterprise.	Y. Wang, Liu, Chan, and Zhang [23]
Management level	Enterprise scale	B1	The larger the enterprise, the more perfect the system, and the higher the credit level of the enterprise.	R. Chi, Yu, and Ruan [24]
	Profitability	B2	The better profitability and the lower the default rate.	Kuang et al. [7]
	Operating capacity	B3	Daily operation and management of the enterprise	Kuang et al. [7]
	Development capacity	B4	The better the future development prospects of enterprises, the higher the credit level.	D. Chen [25]
	Market competitiveness	B5	The enterprise has good strength and brand reputation.	D. Chen [25]
	Risk perception ability	B6	The enterprise can timely judge and avoid risks.	Yu et al. [19]
	Contract performing capability	B7	The enterprise can fulfill the contract on time and has a strong repayment ability.	Kuang et al. [7]
	Organizational ability	B8	The enterprise has strong organizational management ability and can timely identify and solve credit problems.	K. Zhang et al. [3]
Service level	Business duration	C1	The extent to which an enterprise is subject to market inspection reflects the credit level of the enterprise	Kuang et al. [7]
	Platform service	C2	The enterprise can establish a cooperative relationship.	Dai [18]
	Logistics service	C3	The higher the logistic service level of the enterprise, the better the credit status of MSEs.	Liu and Feng [21]
	After-sales service	C4	The more perfect the after-sales service of the enterprise, the higher its credit level.	Liu and Feng [21]
	Value-added services	C5	The more value-added services the enterprise provides, the higher its credit level.	Liu and Feng [21]
	Consumer evaluation	C6	The better consumers evaluate the products and services, the higher the credit level of the enterprise.	X. Wang and Ren [26]

3.2 Determination of the Dynamic Credit Evaluation Weight

3.2.1 Preliminary Determination of Weight

Firstly, based on the traditional method of combining subjective and objective (triangular fuzzy method and CV), the weights are preliminarily determined. The triangular fuzzy method overcomes the lack of consistency in AHP, and experts give three different results for each index, that is, the most conservative, likely, and optimistic results for comprehensive judgment. We set a_{ki} as the most conservative evaluation result of the k expert on the i indicator, b_{ki} as the most likely evaluation result of the k expert on the i indicator, c_{ki} as the most optimistic evaluation result of the k expert on the i indicator, and e_k as the proportion of the evaluation result of the k expert in all experts and calculate the evaluation result T_i of the importance of the i indicator according to Eq. (1).

$$T_i = [a_i, b_i, c_i] = \left[\sum_{k=1} a_i^k e_k, \sum_{k=1} b_i^k e_k, \sum_{k=1} c_i^k e_k \right] \tag{1}$$

The triangular fuzzy score F_i of i indicator is calculated using Eq. (2), and the fuzzy weight s_i of the i indicator is obtained by normalization using Eq. (3).

$$F_i = \frac{a_i + 4b_i + c_i}{6} \tag{2}$$

$$s_i = \frac{F_i}{\sum_{i=1}^{m} F_i} \times 100\% \tag{3}$$

Although the triangular fuzzy method makes up for the deficiency of the traditional analytic hierarchy process in judging consistency, it still has great subjective randomness. CV evaluates and judges the data according to its characteristics, and objectively reflects the differences between the data. The CV z_i of the i indicator is calculated by Eq. (4), $\overline{x_i}$ and δ_i are the average value and standard deviation of the indicator. As shown in Eq. (5), we further calculate the weight v_i of the CV of the $i$indicator.

$$z_i = \frac{\delta_i}{\overline{x_i}} \tag{4}$$

$$v_i = \frac{z_i}{\sum_{i=1}^{3} z_i} \tag{5}$$

Then, the combination weight w_i is calculated according to Eq. (6), that is, the basic weight of the i indicator obtained through the triangular fuzzy and CV methods.

$$w_i = 0.5 s_i + 0.5 v_i \tag{6}$$

The importance of data in different periods to judge the credit level is different, especially in the process of dynamic credit evaluation, the time factor has a great influence on the evaluation results. The time weight is determined according to the importance of the time series. The method for determining the time weight is shown in Eq. (7). λ indicates the preference for time, and its value range is 0-1. The closer it is to 0, the stronger the importance of the recent data, and conversely, the stronger the importance of the historical data.

$$\max \left\{ -\sum_{t=1}^{T} \eta(t) \ln \eta(t) \right\}$$
$$\text{s.t.} \begin{cases} \lambda = \sum_{t=1}^{T} \dfrac{T-t}{T-1} \eta(t) \\ \sum_{t=1}^{T} \eta(t) = 1, \eta(t) \in [0,1] t = 1, 2, \cdots T \end{cases} \tag{7}$$

3.2.2 Weight Optimization Based on System Dynamics and Sensitivity Analysis

To enhance the rationality of the weights, a system dynamics model is established to simulate and analyze the credit evaluation system of MSEs. The role and influence of each part of the system are analyzed using the system dynamics model, and the effects of different feedback loops are determined. The weight is optimized and adjusted according to the simulation results to accurately grasp the credit evaluation results. In this study, we introduce a system dynamics model and further analyze the index sensitivity. The steps are as follows.

1. Establishing Clear Research Objectives: We define the research goals and issues, guiding the research in a focused direction and establishing clear objectives.
2. Identifying Key Factors: We identify the main components within the system and specify the scope of our investigation.
3. Constructing Causal Loops and Diagrams: We create a causal loop and stock-and-flow diagram. These diagrams outline the causality and transmission paths of each internal factor, forming a comprehensive causal loop. Using this loop, we build a stock-and-flow diagram and quantify the variable parameters in the system.
4. Computer Simulation: We employ computer simulations to validate the model's effectiveness. By employing the stock-and-flow diagram, we further refine the quantitative model. Based on simulation results, we adjust the system structure and parameter values to better align with real-world behavioral characteristics.
5. Analyzing Sensitivity: Utilizing the system dynamics simulation outcomes, we fine-tune variable parameters, conduct tests, and observe how variables respond to system behavior. This aids in analyzing the sensitivity of factors that influence the credit evaluation of MSEs in the e-commerce sector.

Sensitivity analysis involves gauging how much the evaluated object is affected by a unit change in the initial value of influencing factors. If a variable significantly impacts the evaluated object under the same change conditions, it is considered more sensitive and important, warranting a higher weight.

We denote X as the influencing factor and Y as the output variable, $X(t)$ and $Y(t)$ represent numerical values at time t, while $\Delta X(t)$ and $\Delta Y(t)$ are denoted variable quantities. We introduce the concept of percentage change to capture the effect between them and derive sensitivity α, indicating the extent of an influencing factor's impact on the credit level, as shown in Eq. (8).

$$\alpha = \left| \frac{\Delta Y(t) / Y(t)}{\Delta X(t) / X(t)} \right| \tag{8}$$

Finally, combined with sensitivity analysis, the comprehensive weight γ_i is calculated. In Eq. (9), α_i and w_i are the sensitivity and basic weight of the i indicator, θ_1 and θ_2 are the weight coefficients of them, and meet $\theta_1 + \theta_2 = 1$.

$$\gamma_i = \theta_1 \alpha_i + \theta_2 w_i \tag{9}$$

3.3 TOPSISC-GRA Dynamic Credit Evaluation for MSEs in E-Commerce

Fig. 1 illustrates the concept of credit evaluation. After determining the indicators based on the characteristics of e-commerce MSEs, the subjective, objective, and time weights are calculated, and the comprehensive weight is obtained through sensitivity weighting. Finally, the ranking results of the credit evaluation are obtained through modeling. We use the TOPSIS-GRA dynamic credit evaluation method, process static data using a dynamic model, and correct data mutation errors on time.

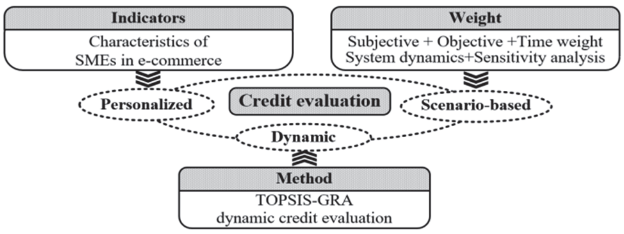


Figure 1 Dynamic credit evaluation process

Based on the traditional TOPSIS evaluation model, risk resistance rewards or punishments are embedded in the basic credit value in the dynamic credit evaluation method and the final evaluation result is obtained according to the credit development tendency [15]. This method ensures that the evaluation result conformes to the actual situation so that the e-commerce supply chain can make timely and accurate decisions and select relatively high-quality partners. The steps are as follows.

1. We determine the risk resistance rewards or punishments based on the traditional TOPSIS model and identify the ability of the evaluated object to resist risks in a specific environment. Eq. (10) represents the anti-risk ability of the evaluated object o_i different from other evaluated objects $o_k \left(k \neq i \text{ and } k = 1, 2, \cdots, n\right)$ at moment t, $y_i(t)$ is the static credit evaluation result calculated at moment t.

$$\Delta y_i(t) = \frac{1}{n-1} \sum_{k=1, k \neq i}^{n} \left\{ y_i(t) - y_k(t) \right\} \quad (k \neq i \text{ and } k = 1, 2, \cdots, n) \tag{10}$$

2. We calculate the positive and negative ideal points from Eq. (11) and (12), respectively.

$$y^+(t) = \max\left\{ y_i^+(1), y_i^+(2), \cdots, y_i^+(t) \right\}, t = 1, 2, \cdots, T \tag{11}$$

$$y^-(t) = \min\left\{ y_i^-(t) \right\}, t = 1, 2, \cdots, T \tag{12}$$

3. We calculate the relative closeness degree C_i, as shown in Eq. (13). Wherein, d_i^+ and d_i^- are the distance from each evaluation subject to the positive and negative ideal points.

$$\begin{gathered} d_i^+ = \sqrt{\sum_{t=1}^{T} \left(y_i(t) - y^+(t) \right)^2}; d_i^- = \sqrt{\sum_{t=1}^{T} \left(y_i(t) - y^-(t) \right)^2} \\ C_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \cdots, n \end{gathered} \tag{13}$$

4. We calculate the gray relation degree ξ_i, and obtain the similarity between the actual dynamic credit sequence and the ideal sequence through the analysis method of GRA, according to Eq. (14).

$$\begin{cases} \xi_i(t) = \dfrac{\min_{i \in n}\left(\min_{t \in T} \left| y^*(t) - y_i(t) \right| \right) + \rho \max_{i \in n}\left(\max_{t \in T} \left| y^*(t) - y_i(t) \right| \right)}{\left| y^*(t) - y_i(t) \right| + \rho \max_{i \in n}\left(\max_{t \in T} \left| y^*(t) - y_i(t) \right| \right)} \\ \xi_i = \dfrac{1}{T} \displaystyle\sum_{t=1}^{T} \xi_i(t) \end{cases}, t = 1, 2, \cdots, T \tag{14}$$

5. We carry out a comprehensive addition to the above results and obtain the dynamic credit evaluation result Z_i, according to Eq. (15). θ and β are the preference coefficients, indicating the degree of preference for the credit development tendency and current credit status of the evaluated object, and $\theta + \beta = 1$.

$$Z_i = \theta C_i + \beta \xi_i \tag{15}$$

4 RESULTS AND DISCUSSION

4.1 Sample Selection

This study considers online merchants in the plant and flower industry on the Chinese Taobao online shopping platform as the research object. We search for the keyword "succulent/green plants" on Taobao and randomly select 20 relevant stores within the industry as the research object according to the screening results, with the numbers D1-D20. The sample structure is as follows. In terms of years of registration, there are 10 stores (50%) in 3-5 years, 9 stores (45%) in 6-10 years, and 1 store (5%) in 11 years. There are 15 stores (75%) whose credit rating of platform sellers is 3 points or above, among which 3 stores (15%) have a credit rating of 5 points. In terms of the number of fans, there are 7 stores with 100,000 or less (35%), 7 stores with 100,000-300,000 (35%), 3 stores with 300,000-600,000 (15%) and 3 stores with 600,000 or more (15%).

Considering the availability of data, the corresponding observed values are added based on the secondary indicators of credit evaluation to refine and improve the indicator system. Standard processing is performed on the original data, and 14 sets of standardized data are obtained.

4.2 Simulation Results of Credit Evaluation System

This study regards each type of influencing factor as a risk subsystem and makes the following assumptions - the credit level of MSEs is only affected by the above risk factors; the policy will not change in a short period; and all entities actively participate in supply chain financing. The risk relationships extend beyond individual subsystems apass interactions and influences among these subsystems, as shown in Fig. 2. The managerial capabilities of MSEs directly impact their credit levels. Meanwhile, the enterprise's product status serves as the foundation for establishing the credit level, and the level of service provided represents an internal influencing factor.

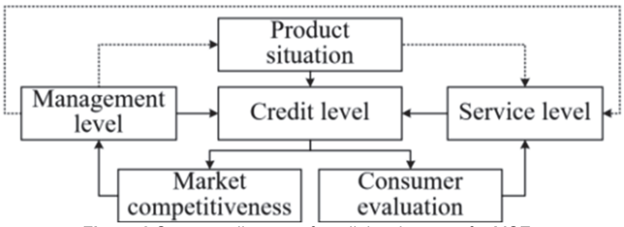


Figure 2 Structure diagram of credit level system for MSEs

VensimPLE software is adopted to identify the mechanism of risk action using the system analysis method. The model flow chart of the formation mechanism of the credit level of MSEs in e-commerce is built, as shown in Fig. 3. Among them, there are 17 main boundary points and two feedback loops. The first feedback loop is market competitiveness - enterprise management level - credit level of MSEs - market competitiveness, and the second is consumer evaluation - enterprise service level - credit level of MSEs - consumer evaluation.

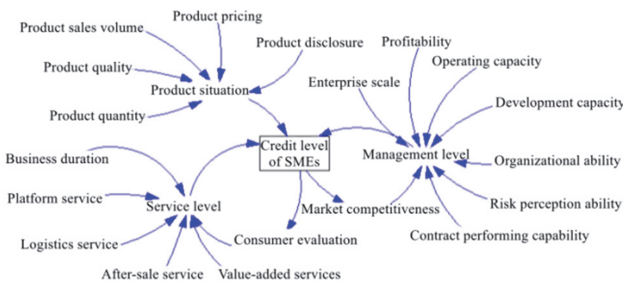


Figure 3 Relationship flow chart of factors influencing the credit level of e-commerce MSEs

In constructing the system dynamics model, it is important to define the system boundaries and establish the initial value. To determine the weights for the system dynamics model, this study quantifies the influencing factors through a questionnaire survey and calculates path coefficients using structural equation models. The initial value for the boundary factor is derived by adding the average value of the data to the error from the structural equation. This value is determined in conjunction with actual data. Fig. 2 features a total of 17 boundary points. Formulas within the model are adjusted accordingly, and initial values for each indicator are assigned. The system dynamics models are developed based on the interplay between indicators, as described in Eqs. (16) to (18).

$$\begin{aligned} &Product\ situation = 0.66 \times Product\ quantity + 0.78 \times \\ &Product\ quality + 0.62 \times Product\ sales\ volume + 0.76 \times \\ &Product\ pricing + 0.53 \times Product\ disclosure \end{aligned} \tag{16}$$

$$\begin{aligned} &Management\ level = 0.66 \times Enterprise\ scale + 0.65 \times \\ &Profitability + 0.56 \times Operating\ capacity + 0.58 \times \\ &Development\ capacity + 0.62 \times Market\ competitiveness \\ &+ 0.68 \times Risk\ perception\ ability + 0.64 \times Contract \\ &performing\ capability + 0.56 \times Organizational\ ability \end{aligned} \tag{17}$$

$$\begin{aligned} &Service\ level = 0.51 \times Business\ duration + 0.67 \times \\ &Platform\ service + 0.75 \times Logistics\ service + \\ &0.79 \times After\text{-}sale\ service + 0.79 \times Value\text{-}added \\ &services + 0.78 \times Consumer\ evaluation \end{aligned} \tag{18}$$

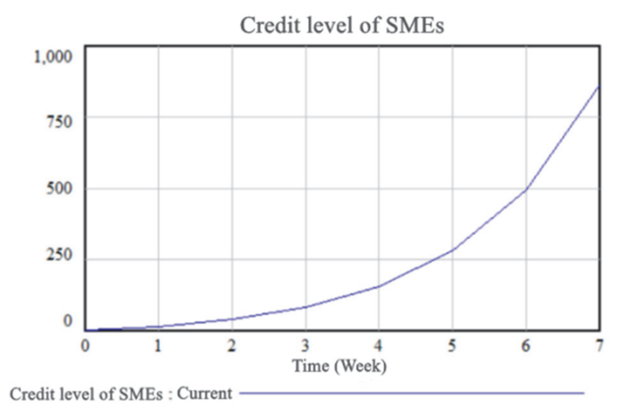
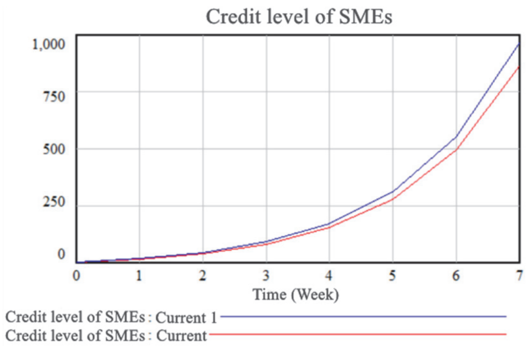
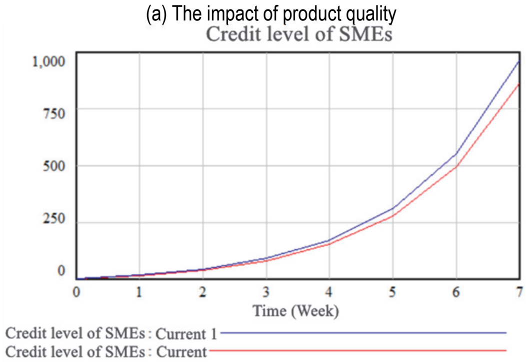


Figure 4 The influence of the single variable on the credit level

The results of the formation mechanism of the credit level of MSEs in e-commerce are shown in Fig. 4. We find that a single variable can promote the credit level of MSEs in e-commerce. We also find that changes in the different influencing factors can increase credit levels. By changing the weight of the influencing factors of the credit level of MSEs on the e-commerce platform, we observe its impact on the change in the output value of the financing credit level of MSEs - that is, it reflects the sensitivity of a certain indicator to risk. As shown in Fig. 5, when the indicator value changes from 0.2 (red line current) to 0.9 (blue line current 1), with an improvement in product quality and risk perception ability, the credit level of MSEs increases, and the impact on the credit level is also greater.



(a) The impact of product quality



(b) The impact of risk perception ability

Figure 5 The influence of different influencing factors on the credit level

4.3 Calculating Indicator Weight

Based on the triangular fuzzy method and the CV, the basic weight is obtained through the combination method. For time weight, we set that $\lambda = 0.2$, indicating that the recent data is of more importance. In the system dynamics model, keeping the values of the other variables unchanged, the initial values of the factors affecting the credit level are taken as 0.2 to get Current 1 and 0.9 to get Current 2. The sensitivity weight of each indicator is calculated with Eq. (8), and the comprehensive weight is calculated with Eq. (9), which is taken as $\theta_1 = \theta_2 = 0.5$. The calculated comprehensive weight is shown in Tab. 2.

4.4 Application of the Dynamic Credit Evaluation Model

The calculation process is as follows. First, the positive and negative ideal points are determined from Eq. (11) and (12). Second, we obtain the ideal trend relation degree and the gray relation degree using Eq. (13) and (14). Third, we obtain the relative risk resistance rewards or punishments for each evaluated object using Eq. (10). Fourth, we determine the weighted decision matrix and their relative closeness degrees after adjusting for rewards and punishments. Finally, considering that the current credit level has been determined, focusing on it will make the results more accurate. Therefore, $\theta = 0.2$ and $\beta = 0.8$ are taken in Eq. (15). Tab. 3 presents the final dynamic credit evaluation results. To emphasize the precision of dynamic credit evaluation, we perform the conventional TOPSIS credit assessment using the most recent data. Subsequently, we compare the static outcomes with the dynamic evaluation results.

Table 2 Comprehensive weight of credit evaluation for MSEs

Index number	Base weight	Sensitivity weight	Comprehensive weight	Index number	Base weight	Sensitivity weight	Comprehensive weight
A1	0.0291	0.0246	0.0269	B6	0.0452	0.0210	0.0331
A2	0.0400	0.0310	0.0355	B7	0.0413	0.0390	0.0402
A3	0.0316	0.0140	0.0228	B8	0.0260	0.0470	0.0365
A4	0.0386	0.0370	0.0378	C1	0.0213	0.0380	0.0297
A5	0.0301	0.0450	0.0376	C2	0.0482	0.0270	0.0376
B1	0.0424	0.0390	0.0407	C3	0.0292	0.0300	0.0296
B2	0.0244	0.0180	0.0212	C4	0.0507	0.0490	0.0499
B3	0.0367	0.0410	0.0389	C5	0.0279	0.0330	0.0305
B4	0.0150	0.0280	0.0215	C6	0.0306	0.0260	0.0283
B5	0.0335	0.0420	0.0378				

Table 3 Dynamic credit rating results

Store	Relative closeness degree	Initial Rank	Development trend similarity	Rank	Dynamic credit	Rank	Static Credit	Rank	Rank on Taobao
D1	0.9414	17	0.4092	17	0.8350	17	0.5889	14	18
D2	0.5746	3	0.3955	2	0.5388	3	0.7126	4	1
D3	0.5660	2	0.3989	4	0.5326	2	0.7854	1	3
D4	0.7999	11	0.4065	12	0.7212	11	0.6106	13	5
D5	0.9455	18	0.4080	14	0.8380	18	0.5757	17	17
D6	0.9190	15	0.4082	16	0.8168	15	0.5658	19	6
D7	0.6068	5	0.3996	5	0.5654	5	0.7361	3	4
D8	0.5817	4	0.3979	3	0.5449	4	0.7629	2	8
D9	0.7670	9	0.4024	8	0.6941	9	0.6455	10	9
D10	0.7048	7	0.4007	6	0.6440	7	0.6887	6	10
D11	0.6398	6	0.4019	7	0.5922	6	0.7069	5	7
D12	0.8952	14	0.4063	11	0.7974	14	0.5725	18	12
D13	0.9274	16	0.4105	18	0.8240	16	0.6132	12	14
D14	0.8252	12	0.4081	15	0.7418	12	0.6404	11	13
D15	0.9523	20	0.4114	20	0.8441	20	0.5888	15	15
D16	0.9502	19	0.4114	20	0.8424	19	0.5299	20	16
D17	0.0000	1	0.3803	1	0.0761	1	0.6456	9	2
D18	0.7472	8	0.4052	10	0.6788	8	0.6482	8	11
D19	0.7698	10	0.4047	9	0.6968	10	0.6540	7	19
D20	0.8547	13	0.4077	13	0.7653	13	0.5774	16	20

Figure 6 Comparison of credit evaluation results

Fig. 6 provides the outcomes of dynamic credit evaluation in comparison to the most recent static credit assessment, while also aligning them with the actual ranking of e-commerce platforms. The dynamic credit ranking curve exhibits a stronger correlation with the actual platform ranking, indicating enhanced consistency with realistic results. For static credit evaluation, the top five are D3, D8, D7, D2, and D11. In contrast, the top five dynamic credit evaluations are D17, D3, D2, D8, and D7. Notably, the top five stores in e-commerce platforms in the actual ranking are D2, D17, D3, D7, and D4. Among the top five, the static credit evaluation results of three stores coincide with those of the e-commerce platform, and the dynamic credit evaluation results of four stores coincide with those of the platform, indicating that both the static and dynamic evaluation models can better evaluate stores on the Taobao platform. The obtained results are consistent with the actual situation. Further comparison shows that the dynamic credit evaluation results are closer to the actual ranking of the platform, indicating that it can reflect the actual situation of the store more comprehensively and accurately and that the evaluation results are more objective.

4.5 Discussion

This research makes several key contributions to credit evaluation and supply chain financing literature: 1) The sensitivity-optimized weighting scheme provides a novel data-driven approach for determining scenario-specific weights. 2) The dynamic evaluation model enables assessing credit trends over time while accommodating new data. 3) The system dynamics simulation deepens the understanding of the credit evaluation mechanism of MSEs in e-commerce and simulates the changing trend of various influencing factors in the actual supply chain financing process. 4) The empirical analysis demonstrates the proposed model's advantages in revealing credit rankings relative to conventional static models.

This study, based on Chinese MSEs, provides insights into credit evaluation and weight optimization methods that can be relevant for other countries. However, adapting these approaches to each country's unique financial landscape is crucial.

The study has important implications for policymakers, researchers, and stakeholders. MSE managers can improve risk management and anticipate, detect, and mitigate risks proactively. E-commerce platforms should establish stronger and more rational evaluation systems to facilitate lending to credit-worthy MSEs. Governments should enforce strict credit oversight, monitor enterprises with weak commercial credit, and consistently regulate MSEs' credit behavior on platforms.

In the future, refining MSE financing evaluation methods within the platform economy is crucial. Incorporating a multi-agent financing model into platform networks can expand the application scope of the evaluation system, making it more effective and sustainable in supporting MSEs' e-commerce financing needs.

5 CONCLUSION

This research addresses key limitations in credit evaluation models for supply chain finance through an innovative dynamic modeling approach using sensitivity-optimized weights. The proposed model integrates subjective, objective, and sensitivity-based methods to determine scenario-specific indicator weights tailored to e-commerce MSEs. A system dynamics simulation identifies the sensitivity of each influencing factor, enabling data-driven weight optimization. The optimized weights are applied in a TOPSIS-GRA dynamic evaluation model to reveal credit trends over time. An empirical analysis demonstrates the model's ability to accurately reflect credit rankings relative to conventional static models. This study provides an effective dynamic modeling technique for credit assessment that enhances supply chain financing efficiency.

The weight optimization results in this paper are tailored to specific e-commerce platform scenarios. In the future, this dynamic credit evaluation method could be used in different scenarios. We might also consider how credit evaluation adapts to the platform economy's financing and involves multiple participants.

Acknowledgement

This research was funded by the Humanities and Social Sciences Research Youth Project of Chinese Ministry of Education (grant number 20YJC630175), Beijing Municipal University Excellent Young Talents Cultivation Plan (grant number BPHR202203222), and General Items of Social Science Plan of Beijing Municipal Commission of Education (grant number SM202211417007).

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