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

Haoyue ZHANG, Ran TIAN, Qi WANG, Dongxiao WU*

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

$$T_i = \left[ a_{i1}, b_{i1}, c_{i1} \right] = \left[ \sum_{k=1}^{m} a_{ki}^k, \sum_{k=1}^{m} b_{ki}^k, \sum_{k=1}^{m} c_{ki}^k \right] \quad (1)$$

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

$$F_i = \frac{a_{i1} + 4b_{i1} + c_{i1}}{6} \quad (2)$$

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

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 $\delta_i$ 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 indicator.

$$z_i = \frac{\delta_i}{\overline{x_i}} \quad (4)$$

$$v_i = \frac{z_i}{\sum_{i=1}^{m} z_i^2} \quad (5)$$

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.

$$w_i = 0.5s_i + 0.5v_i \quad (6)$$

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). $\lambda$ 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.

$$\max \left\{ \sum_{i=1}^{T} \eta(i) \ln \eta(i) \right\}$$

$$\left\{ \begin{array}{l}
\lambda = \sum_{i=1}^{T} \frac{T-t}{T-1} \eta(i) \\
\sum_{i=1}^{T} \eta(i) = 1, \eta(i) \in [0,1], i = 1, 2, \ldots, T
\end{array} \right. \quad (7)$$

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 as variable quantities. We introduce the concept of percentage change to capture the effect between them and derive sensitivity \( \alpha \), indicating the extent of an influencing factor's impact on the credit level, as shown in Eq. (8).

\[
\alpha = \frac{\Delta Y(t) / Y(t)}{\Delta X(t) / X(t)}
\]

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

\[
\gamma_i = \theta_1 \alpha_i + \theta_2 w_i
\]  

(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.

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 conforms 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 \( o_k \) different from other evaluated objects \( o_k (k \neq i \text{ and } k = 1, 2, \ldots, n) \) at moment \( t \).

\[
\Delta y_i(t) = \frac{1}{n-1} \sum_{k=1, k \neq i}^{n} \{y_i(t) - y_k(t)\}
\]

(\( k \neq i \text{ and } k = 1, 2, \ldots, n \))

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

\[
y^+(t) = \max \{y_i^+(1), y_i^+(2), \ldots, y_i^+(t)\}, t = 1, 2, \ldots, T
\]

\[
y^-(t) = \min \{y_i^-(t)\}, t = 1, 2, \ldots, T
\]

(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.

\[
d_i^+ = \sqrt{\sum_{t=1}^{T}(y_i^+(t) - y^+(t))^2} ; d_i^- = \sqrt{\sum_{t=1}^{T}(y_i^-(t) - y^-(t))^2}
\]

\[
C_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \ldots, n
\]

(13)

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

\[
\xi_i(t) = \frac{\min_{r \in \Gamma} \{\min_{s \in \Theta} \{\gamma_i^+(x_s - x_r)\}\} + \rho \max_{r \in \Gamma} \{\max_{s \in \Theta} \{\gamma_i^+(x_s - x_r)\}\}}{\max_{r \in \Gamma} \{\max_{s \in \Theta} \{\gamma_i^+(x_s - x_r)\}\} + \rho \max_{r \in \Gamma} \{\max_{s \in \Theta} \{\gamma_i^+(x_s - x_r)\}\}}
\]

\[
\xi_i = \frac{1}{T} \sum_{t=1}^{T} \xi_i(t), i = 1, 2, \ldots, T
\]

(14)

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.
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).

\[
\text{Product situation} = 0.66 \times \text{Product quantity} + 0.78 \times \text{Product quality} + 0.62 \times \text{Product sales volume} + 0.76 \times \text{Product pricing}
\]

\[
\text{Management level} = 0.66 \times \text{Enterprise scale} + 0.65 \times \text{Profitability} + 0.56 \times \text{Operating capacity} + 0.58 \times \text{Platform service} + 0.62 \times \text{Development capacity} + 0.56 \times \text{Market competitiveness} + 0.64 \times \text{Contract performing capability} + 0.56 \times \text{Organizational ability}
\]

\[
\text{Service level} = 0.51 \times \text{Business duration} + 0.67 \times \text{Platform service} + 0.75 \times \text{Logistics service} + 0.79 \times \text{After-sale service} + 0.79 \times \text{Value-added services} + 0.78 \times \text{Consumer evaluation}
\]

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.
The impact of product quality

The impact of risk perception ability

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>
<thead>
<tr>
<th>Index number</th>
<th>Base weight</th>
<th>Sensitivity weight</th>
<th>Comprehensive weight</th>
<th>Index number</th>
<th>Base weight</th>
<th>Sensitivity weight</th>
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</tr>
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<tbody>
<tr>
<td>A1</td>
<td>0.0291</td>
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<th>Development trend similarity</th>
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<th>Dynamic credit</th>
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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 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 support risk assessment and encourage credit management 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.

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6 REFERENCES


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