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Research Article

A Novel Improved Grey Incidence Model for Evaluating the Performance of Supply Chain Resilience

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Under uncertain conditions, stronger supply chain resilience can effectively reduce disruption risks and help enterprises achieve their goal of high-quality operations. This paper constructs a resilience evaluation index system for manufacturing enterprises from the perspective of the supply chain and uses the improved TOPSIS method to quantify the level of resilience. Taking into account that the resilience index is easily affected by nonconventional factors in the real environment, the WAWBO weakening buffer operator and the metabolism idea are introduced to improve the grey prediction method, so as to realize the dynamic prediction of the resilience index. In addition, a supply chain resilience early warning model is constructed by combining it with the quantification method of resilience. Using the data of a Chinese electronics manufacturing enterprise as a case study, the results demonstrate the effectiveness of the proposed resilience quantification method, and the improved grey prediction method has higher prediction accuracy. The study provides a new idea for relevant enterprises to improve the early warning ability of their supply chain, thus promoting the sustainable development of the supply chain.

1. Introduction

With supply chains (SCs) spanning multiple countries, businesses have enjoyed cost advantages and access to rapidly growing markets. However, managing these complex networks has exposed firms to increase risks of disruptions. The interconnection between global partners can cause disruptions to quickly spread and interrupt the supply chain. As disruptions become more frequent, experts suggest that supply chain resilience (hereafter SCR) capabilities should be developed [1]. Resilience enables supply chains to be event-ready and respond efficiently and effectively to recover from disruptions. Traditional risk management strategies are inadequate for the current highly dynamic environment. Therefore, firms should adopt a resilient orientation to mitigate disruptions amidst increasing uncertainties and associated challenges.

Resilience is defined as the adaptive capability of a system to respond better to disruptions or even gain advantages from such events [2]. It is the property by which a supply chain can reduce, react to, and overcome potential risks and vulnerabilities. A resilient supply chain can quickly adapt to changes in demand, supply, and market conditions, allowing enterprises to respond to new opportunities, optimize their operations, and improve their competitiveness [3]. Hence, a strong SCR can assist manufacturing companies in achieving robust operational performance and sustainable growth in unpredictable environments [4].

Existing literature suggests that certain attributes, known as enablers, are crucial for enhancing SCR and have a positive impact on the risk mitigation environment. These enablers include visibility, robustness, agility, flexibility, collaboration, organizational culture, innovation, and top management commitment [5–7]. They have been shown to improve financial performance, situational awareness, quick response, adaptability, and recovery during disruptions. Quantitative assessments of resilience using enablers and their interdependencies are useful tools for managers to measure, manage, and control SC resilience [8, 9]. Employable quantitative measures of resilience are advantageous in computing the quality of SC resilience to mitigate disruptive events and provide a method for benchmarking and comparing resilience capabilities with other SCs.

In parallel, existing studies have well documented that the resilience level of a manufacturing enterprise supply chain can be measured by multiattribute decision-making (MADM) methods [10, 11]. Multiattribute decision-making (MADM) methods are a set of techniques used to evaluate and rank alternatives based on multiple criteria or attributes. These methods are commonly used in decision-making contexts where there are multiple, conflicting objectives or criteria that must be considered. There are many different MADM methods, including weighted sum models, analytic hierarchy process (AHP), ELECTRE, PROMETHEE, and TOPSIS. For example, Pournader et al. [12] established a supply chain risk resilience evaluation framework by combining the fuzzy set theory and data envelopment analysis (DEA). Lotfi et al. [13] utilized an improved fuzzy comprehensive evaluation method to assess the resilience of the healthcare supply chain. The technique for order preference by similarity to an ideal solution (TOPSIS) method is widely employed as an effective approach in multiobjective decision analysis. It is not restricted by sample size or indicators, making it suitable for comprehensive evaluations across diverse scenarios. Ama et al. [14] proposed a fuzzy multiobjective programming model for green resilience and combined fuzzy AHP and TOPSIS methods to evaluate the resilience of the supply network. Menon and Ravi [15] employ a combined AHP-TOPSIS multiple criteria decision-making approach to consider the uncertainty involved in evaluating both quantitative and qualitative data and conclude that economic factors still dominate during sustainable supplier selection.

In an uncertain environment, SCR is not long-term stable, and through early warning signals, enterprises can timely make strategic adjustments to reduce the possibility of interruption. However, conventional quantitative analysis methods make it difficult to achieve accurate prediction in an uncertain environment. Moreover, enterprise resilience indicators are significantly impacted by recent data, and the grey system theory offers higher accuracy in predicting uncertain information with a small database. Grey system theory is a mathematical framework for modeling and analyzing systems with incomplete or uncertain information. The basic idea behind grey system theory is to use a small amount of available information to make predictions and decisions. In this way, the grey system theory provides a useful tool for dealing with problems that cannot be modeled using traditional mathematical methods. By incorporating both known and unknown information into the analysis, grey system theory can help researchers and practitioners make more informed decisions in complex and uncertain environments [16].

The limitations of current research on SCR mainly lie in the following two aspects. First, most existing research regards resilience as a constant value, ignoring the characteristic of resilience fluctuating with time from a microperspective. Second, there is a lack of analysis of the evolution of resilience in manufacturing enterprises from the perspective of the supply chain and the use of scientific methods to predict the resilience level for early warning. To address these concerns, this study selects resilience evaluation indicators from three perspectives of responsiveness, adaptability, and recovery according to the characteristics of manufacturing enterprise supply chains and quantifies the resilience level of the supply chain with the TOPSIS method. In the resilience warning model, the idea of weakening buffer operators and metabolism is introduced into the grey prediction method, and a resilience warning model of manufacturing enterprise supply chains is constructed. The weakening buffer operators can effectively weaken the impact disturbance of the system and restore the original appearance of the system, and the advantage of the metabolism model for grey prediction is its ability to provide accurate forecasts even when there is limited data available, making it a useful tool for decision-making [17]. Finally, a case study is conducted based on the data of an electronic manufacturing enterprise from 2020 to 2022 to provide implications for related manufacturing enterprises to achieve the goal of high-quality management.

The rest of this paper is laid out as: Section 2 introduces the SCR evaluation index system. Section 3 establishes the SCR warning model. Section 4 provides a case study using the method proposed, while the last section concludes the paper.

2. SCR Evaluation Index System

The extant literature on the evaluation of enterprise resilience is multifaceted, including collaboration, visibility, security redundancy, market position, partnership, etc. [18–20]. For manufacturing enterprises, SCR is essential for their high-quality and sustainable development. Therefore, this study aims to uncover the factors affecting the level of resilience from the following aspects, namely, response ability, adaptation ability, and recovery ability. These three dimensions correspond to the pre-, in-, and postevent stages of the uncertain event, respectively.

(1) *Response Capability*. Response capability stresses the supply chain's capacity to respond quickly to unknown risks by promptly sensing changes in the external environment in the purchasing, production, and delivery processes. The ability to respond quickly to changes in market demand or supply is crucial for supply chain response capability, and it is closely related to agility and collaboration. Enterprises need to be agile in order to effectively respond to uncertain risks, while collaboration is essential for achieving this goal. According to [21], agility can be proxied by two subindicators: delivery lead time and order response speed. Collaboration capability emphasizes the importance of reducing uncertain risks and enhancing service levels through the sharing of information and the use of technology among partners who work together. When collaboration capability is low, it suggests that the production and delivery capabilities of cooperating enterprises may not meet the necessary requirements, or that the organizational management of these enterprises may not be able to keep up with the demands of enterprise

operations. In line with [22, 23], we select information sharing, on-time delivery of materials, and material qualification rate as the three subindicators corresponding to the collaboration factor.

(2) *Adaptation Capability*. Adaptation capability emphasizes the maximum bearing capacity of the supply chain to maintain normal operation under external disturbances, including two indicators: flexibility and safety redundancy. Supply chain flexibility refers to the capacity to swiftly adapt operational plans in response to emergencies, taking into account demand and environmental conditions. The subindicators that make up flexibility include capacity utilization and regional warehouse finished product inventory, according to [24, 25]. The safety redundancy index reflects the ability of enterprises to reduce interruption risks by strategically using excess reserve resources to improve the response to unexpected risks. The subindicators that make up safety redundancy at the third level include finished goods inventory and key material inventory [26].

(3) *Recovery Capability*. Recovery capability indicates that the supply chain can quickly recover to normal operations after the interruption risk occurs. After the interruption, decision-makers need to reallocate resources, adjust supply chain strategies, etc. to quickly restore the supply chain to normal status. Recovery capability includes emergency capability and logistics support in the supply chain. Emergency capability indicates that enterprises establish emergency mechanisms by reallocating resources and monitoring information to improve recovery capability after operations are interrupted. Based on [27, 28], we incorporate alternate suppliers, on-time deliveries, and qualified rates of finished products as secondary indicators of the emergency capabilities. Logistic support can provide guarantees for product transportation and distribution in the interruption.

Drawing from the analysis above, we have identified the SCR indicators for manufacturing enterprises and have developed a corresponding evaluation index system, which is presented in Table 1. Furthermore, when selecting resilience indicators, it is important to consider factors such as data availability and data analysis usability. This ensures that the chosen indicators not only accurately reflect the SCR of enterprises, but also allow for predictions based on indicator data collected at different times.

3. SCR Warning Model

3.1. Fuzzy Analytical Hierarchy Process. When the number of indicators is large, the traditional AHP method is more likely to cause consistency problems in subjective weighting. Therefore, a stream of studies has extended the AHP method to fuzzy conditions and presented the fuzzy analytic hierarchy process (FAHP) to construct a fuzzy consistency judgment matrix [29]. The FAHP procedure is an effective way to address the issue of inconsistency among experts when determining weightings. This helps to ensure that weight distribution is more reasonable and accurate. According to Chamoli [30], the typical FAHP model mainly includes the following four steps: set up the hierarchical structure model, establish the fuzzy complementary judgment matrix, solve the weight of fuzzy complementary judgment matrix, and test the consistency.

3.2. TOPSIS Method. TOPSIS (technique for order preference by similarity to an ideal solution) method proposed by Hwang and Yoon is a commonly used effective method in multiobjective decision analysis, also known as the superiority-inferiority distance method [31]. This method is an ordering method that approximates an ideal solution. The method only requires each utility function to have monotonically increasing (or decreasing) properties. The TOPSIS method involves quantifying evaluation objects by measuring the Euclidean distance between each solution and the positive/negative ideal solution. The determination of the positive/negative ideal solution is typically based on the optimal and worst values of each indicator. However, in real-world enterprise environments, resilience indicators may not always reach the ideal state. To address this issue, we have improved the model by manually setting the optimal and worst values. This allows the model to better reflect the current SCR levels of enterprises. The improved TOPSIS method can be described as follows.

To begin with, the optimal and worst solution sets for the indicators need to be determined based on industry standards and expert opinions, respectively, denoted as $A = [y_1^+, y_2^+, \ldots, y_j^+]$ and $B = [y_1^-, y_2^-, \ldots, y_j^-]$, $j = 1, 2, \ldots, n$, where for the negative indicator j, the optimal solution y_j^+ should not be larger than y_j^-.

Second, normalize matrix $P_{m\times n}(p_{ij})$ to obtain the feature matrix $N_{m\times n}(n_{ij})$, where p_{ij} denotes the value of index j for enterprise at time i:

$$n_{ij} = \frac{p_{ij} - y_j^-}{y_j^+ - y_j^-}. \tag{1}$$

Third, the weighted feature matrix $V_{m\times n}(v_{ij})$ can be calculated by $V_{m\times n} = N_{m\times n} \times W_{m\times n}$, where $W_{m\times n}$ is the index weight matrix obtained through the fuzzy analytic hierarchy process (FAHP).

Fourth, compute the Euclidean distance between each index, and we can obtain the positive and negative ideal solutions as follows:

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^{n} \left(v_{ij} - V_j^+\right)^2}, \quad (i = 1, 2, \ldots, m), \\ d_i^- &= \sqrt{\sum_{j=1}^{n} \left(v_{ij} - V_j^-\right)^2}, \quad (i = 1, 2, \ldots, m), \end{aligned} \tag{2}$$

where V_j^+ and V_j^- denote the maximum and minimum values of each column of the feature matrix $V_{m\times n}$, respectively.

Table 1: Manufacturing enterprise SCR evaluation index system.

Dimensions	Primary indicators	Secondary indicators	Symbols
Reaction capability	Agility	Delivery lead time	R_1
		Order response speed	R_2
	Collaboration	Information sharing	R_3
		On-time delivery of materials	R_4
		Material qualification rate	R_5
Adaptation capability	Flexibility	Capacity utilization	R_6
		Regional warehouse finished product inventory	R_7
	Safety redundancy	Finished goods inventory	R_8
		Key material inventory	R_9
Recovery capability	Emergency capability	Alternate supplier	R_{10}
		On-time delivery of finished products	R_{11}
		Qualified rate of finished products	R_{12}
	Logistics support	Logistics capability	R_{13}

Lastly, score the indicators at the decision time i by $c_i = d_i^- / (d_i^+ + d_i^-)$, where $c_i \in [0,1]$, the higher c_i is, the stronger the resilience at time i is.

3.3. Improve Grey Prediction Method. From a macro perspective, enterprise supply chains tend to remain fairly stable in terms of resilience. However, when we zoom in and examine things on a smaller scale, SCR can be more susceptible to fluctuations caused by unconventional factors. Furthermore, traditional prediction methods like neural networks, which heavily rely on historical data to forecast future states, are unable to provide accurate predictions for enterprise resilience due to the relatively minor impact of historical data on future states. In comparison, the grey prediction method allows the modeller to predict future states of SCR with limited grey information under the circumstance of information uncertainty and a relatively small sample set.

The enterprise resilience index is usually subject to interference from uncertain factors, which often results in faster or slower evolution trends. However, the grey prediction method has low accuracy for predicting nonsmooth sequences. Hence, by incorporating a weakened buffer operator to adjust the original sequence, it becomes feasible to predict the random fluctuation patterns of the sequence, thereby significantly enhancing the prediction accuracy. The improved grey prediction method can be described as follows:

Step 1: Given a time series $X = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ of the resilience index r, where $x^{(0)}(i) > 0\,(i = 1, 2, \ldots, n)$, r represents the resilience index to be predicted, and n represents the number of prediction samples. The ratio $\sigma(k)$ is calculated to determine whether the sequence data can be used for grey prediction, where $\sigma(k) = x^{(0)}(k-1)/x^{(0)}(k)$, $k = 1, 2, \ldots, n$. If $\sigma(k) \in (e^{-(2/(n+1))}, e^{2/(n+1)})$, the ratio test is passed.

Step 2: If the original sequence does not pass the ratio test, the weighted average weakness buffering operator (WAWBO) D is introduced to modify the raw database. We obtain the modified sequence $\widetilde{X} = (\widetilde{x}^{(0)}(1), \widetilde{x}^{(0)}(2), \ldots, \widetilde{x}^{(0)}(n))$. Re-execute Step 1, then proceed to Step 3 if it passes the ratio test, where

$$x^{(0)}(k)d = \frac{2}{(n+k)(n-k+1)}\left[kx^{(0)}(k) + (k+1)x^{(0)}(k) + \ldots + nx^{(0)}(n)\right], \quad k = 1, 2, \ldots, n. \tag{3}$$

Step 3: Establish the GM (1, 1) model. Perform an accumulative operation on the corrected sequence $\widetilde{X}$ to generate a sequence $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$, where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$, $k = 1, 2, \ldots, n$

Then, the whitening function of GM (1, 1) can be given as follows:

$$\frac{\mathrm{d}X^{(1)}}{\mathrm{d}t} + aX^{(1)} = \mu, \tag{4}$$

where a denotes the develop grey scale, while μ is the control grey scale. Equation (4) can be simplified to $\widetilde{x}^{(0)}(k) = \mu - az^{(1)}(k)$.

Estimate the parameters of the equation using the least squares method, then, the parameters a and μ to be estimated satisfy $\widehat{u} = (a, \mu)^T = (B^T B)^{-1} B^T M$.

Solve the parameter, take $x^{(1)}(0) = x^{(0)}(1)$, we can obtain the time response sequence of the grey differential equation as follows:

$$x^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{\mu}{a}\right]e^{-ak} + \frac{\mu}{a}. \tag{5}$$

To obtain the final prediction result, perform a cumulative subtraction reduction on the acquired sequence:

$$\begin{aligned}\hat{x}^{(0)}(k+1) &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= \left[x^{(0)}(1) - \frac{\mu}{a}\right](1-e^{a})e^{-ak}.\end{aligned} \tag{6}$$

Step 4: Metabolic grey prediction. The conventional grey prediction method is based upon the historical static data before t time for prediction. However, under realistic conditions, with the continuous addition of new grey information into the prediction system, the amount of information contained in the longer data is less, so the use of grey theory for prediction will cause the accumulation of errors. The metabolic grey prediction model can dynamically incorporate real-time information into the grey prediction, enabling dynamic sequence prediction and reducing prediction errors effectively.

To predict the original data with a quantity of n, a metabolic grey prediction model needs to select the data of time t to predict the data of time $t+1$. By dropping the oldest data $x^{(0)}(1)$ and adding the new data $x^{(0)}(t+1)$, an updated model is obtained, and then Step 3 is repeated to obtain a metabolic renewal. By continuously updating the data sequence to predict the data at $t+1$ time, a new prediction sequence is established. When $t+1=n$, the predicted data $x^{(0)}(n+1)$ can be added to the original sequence and using the available information, the subsequent data can be predicted to determine the developmental trend of the data. This can help enterprises adjust their strategies in a timely manner.

Step 5: Testing the model prediction error. Since the model requires multiple iterations, the mean absolute percentage error (MAPE) model is chosen for testing its effectiveness.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{x}_i - x_i}{X_i}\right| \times 100\%, \tag{7}$$

where n is the number of predicted samples, and x_i and $\hat{x}_i$ are the real value and the predicted value of the SCR index at time i.

3.4. SCR Early Warning Model. Based on the resilience evaluation index system, the fuzzy hierarchical analysis method is used to determine the weight of the index, and the improved TOPSIS method is performed to accurately quantify the resilience level of the supply chain. To timely perceive the change in SCR, we propose an improved grey prediction model to forecast the resilience features in the future time and combine it with the resilience quantification method to analyze the dynamic of enterprise SCR. This can assist decision-makers in making timely supply chain strategy adjustments, thereby mitigating the risk of disruptions. In addition, through the feedback on the implementation results of the supply chain strategy, it also helps decision-makers realize the dynamic optimization process of the supply chain. The process of the manufacturing enterprise SCR early warning framework is illustrated in Figure 1.

4. Case Study

This study takes a Chinese electronics manufacturing company as a case to verify the effectiveness of the proposed early warning model. This company is a worldwide leader in security product manufacturing, but has faced challenges due to the rapidly changing external environment, including international supply chain disruptions and the COVID-19 crisis. To tackle this issue, the company requires an early warning mechanism for SCR that can monitor and forecast changes in real-time and support decision-makers in adapting operations as needed. Through interviews with supply chain directors, we discovered that data on resilience indicators was available. We then selected a representative product line and collected data on 13 resilience indicators from 30 monthly time nodes. We replaced some indicators with relevant ones and determined optimal and worst solutions for each index based on industry expertise. The data was then preprocessed through normalization.

4.1. Measure for SCR. For the sake of simplicity, only two-level hierarchy structure consisting of dimensions and second-level indicators is considered here due to the complexity of the three-level structure. According to the scoring method of the five-level method, an expert questionnaire is designed to compare the importance of each indicator. Then, the weights of each indicator are calculated using the FAHP method, as shown in Table 2.

Then, the resilience distribution of the enterprises from 2020 to 2022 is obtained by using the improved TOPSIS method, as illustrated in Figure 2.

As illustrated in Figure 2, the SCR of the considered enterprise is relatively strong, with the resilience distribution ranging from 0.45 to 0.70 in 2020–2022, and the majority of the time nodes having resilience levels higher than 0.5. However, the enterprise's SCR performance is relatively weak, with approximately one-third of the total sample falling within the 0.55–0.60 range across multiple time nodes. This may be attributed to the combined pressures of domestic and foreign environmental factors during the past two years and the impact of uncertain factors, which highlights the need for further improvements in enterprise resilience.

4.2. Grey Prediction. Since some flexibility indicators are relatively stable over a certain period of time, we focus on predictive indicators that are easily affected by external factors and forecast the flexibility indicators for the next three months based on two years of historical data. The selection of flexibility features and some raw data are shown in Table 3.

After preliminary analysis of the data sequence, it suggests that the database is a nonsmooth sequence and the range of data change is large, resulting in the failure of the model to pass the class-compare verification. However, we are able to successfully address this issue by introducing the weakened buffer operator to modify the original data

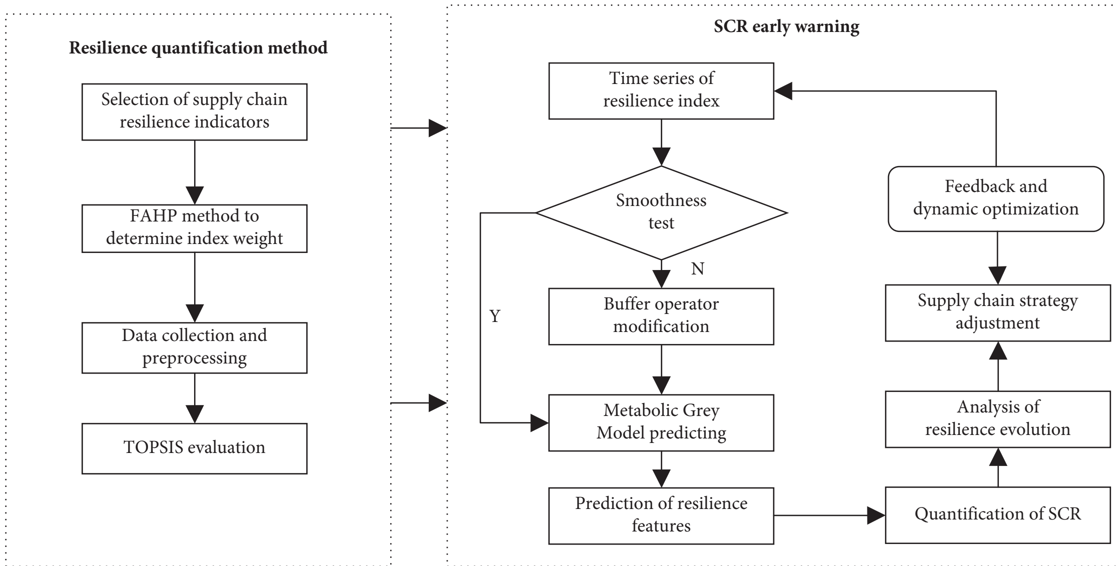

Figure 1: SCR early warning model framework.

Table 2: SCR index weight.

Primary indicator		Secondary indicator		
Dimensions	Local weight	Resilience index	Local weight	Global weight
Reaction capacity	0.5165	Delivery lead time (R_1)	0.2643	0.1367
		Order response speed (R_2)	0.2576	0.1261
		Information sharing (R_3)	0.1645	0.0861
		On-time delivery of materials (R_4)	0.1654	0.0856
		Material qualification rate (R_5)	0.1587	0.0851
Adaptation capability	0.2563	Capacity utilization (R_6)	0.2576	0.0656
		Regional warehouse finished product inventory (R_7)	0.2571	0.0613
		Finished goods inventory (R_8)	0.2418	0.0645
		Key material inventory (R_9)	0.2464	0.0643
Recovery capability	0.2313	Alternate supplier (R_{10})	0.2545	0.0545
		Logistics capability (R_{13})	0.2367	0.0555

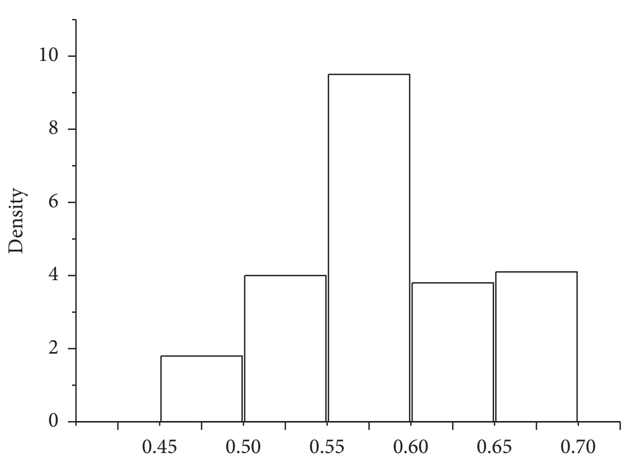

Figure 2: Distribution diagram of enterprise SCR.

sequence. Subsequently, we employed three different models: traditional GM (1, 1), WAWBO with buffer operator GM (1, 1), and improved GM (1, 1) based on metabolism to predict the related resilience indicators. The metabolism cycle t is set to 6 months, and the accuracy of the model is tested by the mean absolute percentage error (MAPE). The specific results are shown in Table 4.

According to Table 4, the prediction accuracy of the grey prediction method can be greatly improved by using the WAWBO weakening buffer operator to modify the raw database. We find that the prediction results of the modified grey prediction model were significantly lower than those of the traditional grey prediction method in terms of mean absolute error, from 24.11% to 4.13%. Furthermore, the implementation of the metabolism method can eliminate the impact of long-term data on prediction results and lead to improved prediction performance.

4.3. Evolution of SCR. Using the improved grey model discussed earlier, we predicted the resilience indicators for the period from October 2022 to December 2022 and quantified the future enterprise SCR. This enables us to track the evolution of enterprise SCR since January 2020, as depicted in Figure 3.

Table 3: Raw data for resilience indicators.

Time	R_2	R_4	R_6	R_8	R_9	R_{11}	R_{13}
2020/01	0.913	0.7123	2867	4001	25654	0.92	2786
2020/02	0.91	0.2013	795	5376	16856	0.83	1476
2020/03	0.92	0.6576	3192	2767	15656	0.851	2187
2020/04	0.93	0.9123	4325	3001	22675	0.812	2233
2020/05	0.933	0.8565	5676	2898	200122	0.867	2576
2020/06	0.926	0.8785	5786	2701	196787	0.917	2514

Table 4: Comparison of prediction errors among different models.

Index	Standard GM (1, 1)	WAWBO-GM (1, 1) model	New GM (1, 1)
R_2	3.02	0.96	0.69
R_4	9.69	2.89	1.94
R_6	27.97	4.26	4.45
R_8	20.21	5.61	3.35
R_9	46.99	3.99	2.71
R_{11}	17.45	3.29	2.55
R_{13}	38.63	7.79	4.67
Prediction error	24.11	4.13	2.31

As demonstrated in Figure 3, the SCR of the enterprise has been unstable due to factors such as international product competition and economic conditions, resulting in significant variations in resilience at certain points. We particularly notice that the SCR of the enterprise reaches its lowest point in August 2021, due to the influence of the government demand side of the security industry. Despite the short-term sharp fluctuations, the main trend of the SCR of the enterprise has been rising, reaching a new high in March 2022. This highlights the fact that decision-makers can effectively enhance the enterprise's ability to deal with uncertain risks by making operational strategy adjustments aimed at improving the resilience level.

It also suggests that the resilience of the enterprise has been on a downward trend since March 2022. This can be mainly attributed to the international further policy sanctions that businesses were facing at that time as well as the impacts of the COVID-19 pandemic on the supply chain on both the supply and sales sides. However, with the relatively stable epidemic situation in China since June 2022, the release of government demand accelerated, while the enterprise also adjusted its supply chain strategy, gradually increasing the resilience of the enterprise supply chain since July. Therefore, this paper explores the evolution trend of resilience from the three dimensions of reaction ability, adaptation ability, and recovery ability, as shown in Figure 4.

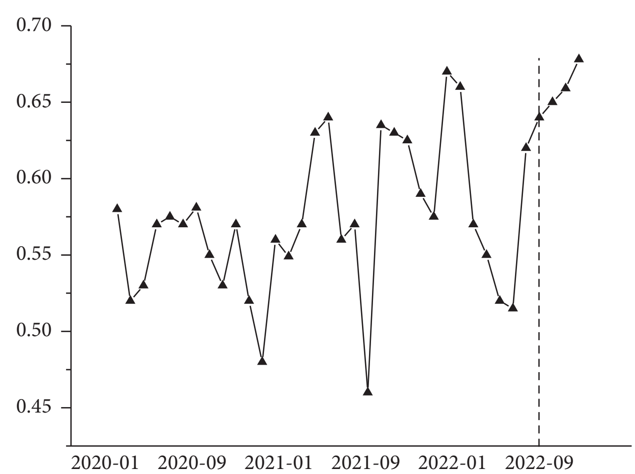

Figure 3: Evolution of SCR.

Since March 2022, the rapid decline in responsiveness has led to a gradual decrease in SCR, however, with the rapid recovery of responsiveness since July, the level of resilience has improved significantly. This appearance indicates that responsiveness is the main reason for the variation in SCR. In addition, it suggests that the performance of adaptability is relatively stable. At the start of 2021, the enterprise significantly improved its adaptability by adjusting its inventory strategy to mitigate supply chain risk through high inventory levels, as depicted in the adaptability curve in Figure 4. By comparing the recovery curves in Figures 3 and 4, we can observe that when the enterprise's resilience begins to decline, the recovery level is typically higher, indicating that recovery capability plays a crucial role after a risky event has occurred.

Although the resilience level of the supply chain is gradually increasing in the next three months, the overall resilience performance is not strong enough. Therefore, enterprises still need to maintain a high level of crisis awareness, retain high responsiveness through improving supply chain strategies, such as improving order processing speed and improving supplier quality. Besides, measures such as inventory adjustment and the risk response plan should be taken to enhance the adaptive capacity and recovery capacity of the supply chain, so as to further enhance the resilience level of the supply chain of the enterprise.

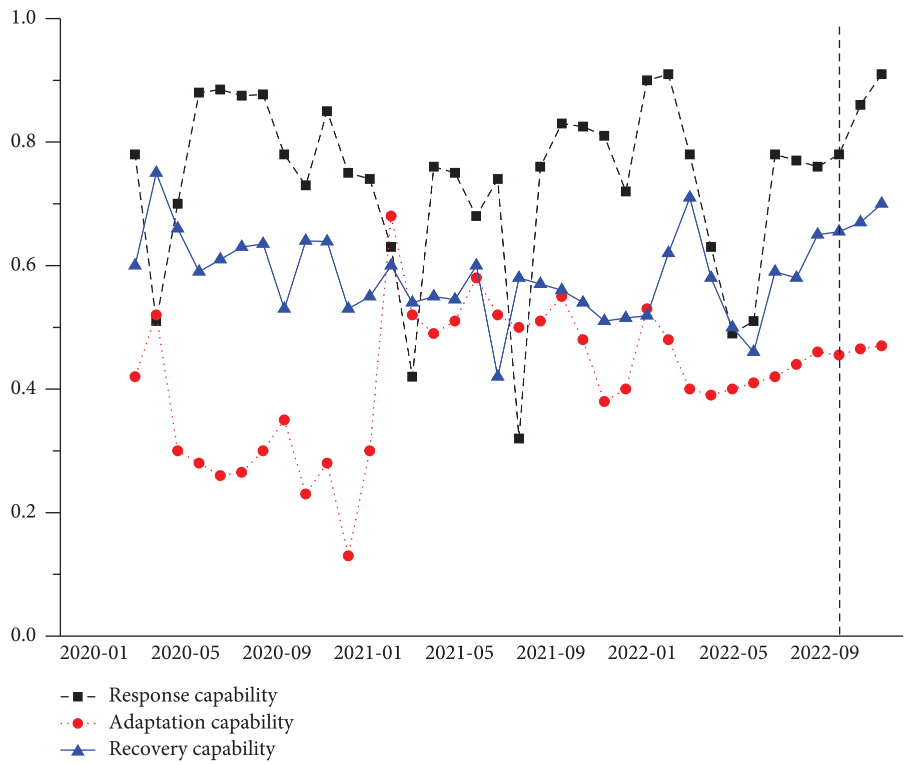

Figure 4: Evolutionary characteristics of various dimensions of resilience.

The prediction results and strategy recommendations mentioned above were validated through subsequent visits to the enterprise. During the most recent visit on September 26, 2022, the supply chain director provided feedback that the company is currently experiencing a decrease in response speed on both the demand and supply side due to measures taken for epidemic prevention and control, as well as changes in the international business environment. However, the enterprise is actively making strategic adjustments to address these challenges. This feedback further confirmed the practicality and feasibility of the study.

5. Conclusion

The resilience theory provides a valuable complement to traditional risk management, allowing enterprises to proactively identify potential supply chain risks. This study has quantitatively calculated enterprise SCR by establishing an evaluation indicator system for manufacturing enterprises. Unlike prior studies, this research evaluates SCR and predicts future enterprise resilience based on historical data, while analyzing the time-varying of resilience level across multiple dimensions. By establishing an early warning model for manufacturing enterprises' SCR, changes in resilience and their causes can be identified in real-time, providing decision-makers with a basis for adjusting operational strategies promptly to improve their capacity to react to market condition changes and avoid the risk of disruption.

We conducted a case study based on actual data from a Chinese electronic manufacturing company and found that this method achieved excellent results in practical applications. The analysis indicates that the company's supply chain resilience was severely affected during the COVID-19 pandemic and urgently needs improvement. Further analysis also shows that the FAHP-TOPSIS method proposed in this paper can effectively measure and evaluate supply chain resilience. Moreover, our method can handle data fluctuations better, making it suitable for predicting resilience indicator data. In summary, this study expands the application of grey forecasting models in the field of supply chain resilience (SCR) and proposes solutions for SCR early warning, prevention, and response.

Data Availability

The data that are used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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